The Political Economy of Automation and Fragmented Production: Evidence from Mexico*

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Abstract

How does automation in the Global North shape politics and violence in the Global South? We develop a political economy theory in which robot adoption in advanced economies reduces demand for export-oriented labor in developing countries, depressing wages and employment and creating social and political consequences. We test this argument in Mexico, a close trade partner of the United States. Using commuting-zone data, we construct exposure measures combining pre-NAFTA export employment with U.S. industry robot growth and initial offshoring intensity, while accounting for domestic robot adoption and other shocks. To address endogeneity, we instrument foreign exposure with European robot diffusion. We find that regions more exposed to foreign robots experience higher levels of violent organized crime, including narcocrime and homicides (but not property crime), and stronger support for left-populist candidates. These findings demonstrate how automation shocks ripple through global value chains to reshape society and elections.

Keywords: automation, offshoring, Global South, violence.

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1 Introduction

The acceleration of automation has reshaped employment, wages, and international production, with ramifications for political attitudes and party alignments. Economic research shows that new technologies raise firm competitiveness and labor productivity (e.g., Koch et al., 2021; Bonfiglioli et al., 2024). At the same time, automation has reduced labor's share of income, contributed to unemployment and wage stagnation among low-skilled workers, and polarized labor markets by shrinking middle-wage jobs in developed countries (e.g., Autor et al., 2003; Goos et al., 2009), accounting for a large share of recent shifts in the U.S. wage distribution (Acemoglu and Restrepo, 2022).

Mostly relying on evidence from advanced economies, current research shows also that these disruptions correlate with changes in political behavior, including higher disengagement (Boix, 2019; Gonzalez-Rostani, 2024a), greater support for populist and radical-right parties (Owen, 2019; Kurer, 2020; Anelli et al., 2021; Gonzalez-Rostani, 2025), and stronger demands for redistribution and protection (Busemeyer et al., 2023; Kurer and Häusermann, 2022; Chaudoin and Mangini, 2025; Gonzalez-Rostani, 2024b). However, we know far less about the social and political consequences of automation for the Global South. Accordingly, the goal of this paper is to examine how technological change, mainly operating through foreign automation, is reshaping export flows and labor market and, with them, the politics of the Global South.

In a world of dense global value chains (GVCs), technological change in one region can reshape production and employment elsewhere. Emerging markets gained from offshoring during the 1990s and 2000s. However, recent technological changes now threaten those gains. Input sourcing from developing countries tripled in the early 2000s but then slowed down after 2011 as automation eroded the advantage of low-wage labor (e.g., Faber et al., 2023). Robots can now perform tasks once offshored, spurring reshoring and altering GVC structures

(De Backer et al., 2016; Rodrik, 2018a; Lund et al., 2019). By way of example, consider three cases that showcase how automation in labor-intensive, offshorable economic activities can displace developing-country workers and weaken the employment gains once associated with globalization. Caterpillar adopted 3D printing in 2012, which allowed it to reshore from China and cut production costs by 90% (Rasmussen, 2016). In 2016, Ford relocated 3,250 jobs from Mexico to Michigan and Ohio. Finally, even though United Technologies (Carrier) initially planned to move a plant from Indianapolis to Mexico, a stream of federal subsidies persuaded it to stay in the United States. Yet, rather than preserving domestic jobs or creating new ones abroad, Carrier invested those subsidies in automation, reducing labor demand on both sides of the border. As the CEO explained, "We're going to automate to drive the cost down so that we can continue to be competitive" (Isidore, 2016).

A growing strand of economic research finds that the adoption of labor-saving technologies in advanced economies (hereafter "foreign robots" when analyzing effects on developing countries) results in a decline in the relative cost of producing at home, a slowing down of offshoring, the reshoring of industrial production to the North, and the contraction of demand for Southern export-oriented manufactures. Even when these changes may increase the demand for imports of products based on non-automated tasks in the Global South, the overall displacement of manufacturing workers in the latter heightens economic insecurity, pushing workers toward lower-quality jobs or unemployment. Indeed, there is mounting evidence associating foreign automation with lower labor demand, wage stagnation, and job losses in the Global South (e.g., Artuc et al., 2019; Faber, 2020). Countries specializing in labor-intensive tasks, such as Mexico, India, Bangladesh, and Vietnam, seem to be particularly exposed. Trade effects point to a reordering of what and how goods move across borders: demand for manufactured imports from developing countries falls (Hidalgo and Micco, 2024), while demand for complementary inputs such as minerals and agricultural goods rises (Stemmler, 2023). In some settings, these forces offset each other, leaving net trade balances largely unchanged (e.g., Artuc et al., 2023).

Where labor markets are slack and safety nets are thin, these shocks arguably have important social and political consequences. On the one hand, they affect public safety and the state's provision of order. More precisely, some displaced workers may enter informal or illicit activities, increasing crime and violence where there are criminal organizations and weak police enforcement. On the other hand, they reshape the electoral market. Voters in exposed communities may move away from establishment parties associated with pro-market, globalization agendas and become more supportive of candidates who promise redistribution, social protection, and state-led industrial policies.

Empirically, we examine the effects of foreign robot adoption on violence in Mexico (1990–2020) and on presidential vote shares (2006–2024) at the commuting-zone level. Mexico provides a compelling case for analyzing how automation-driven economic disruptions in advanced economies affect developing countries because its economy is relatively well integrated with the United States. Following the approaches of Acemoglu and Restrepo (2020) and Faber (2020), we construct measures of local exposure to both domestic and foreign automation. Specifically, we rely on the initial distribution of export-oriented employment across Mexican industries with two factors: (1) industry-level trends in U.S. robot adoption and (2) the initial U.S. reliance on imports from Mexico. We then estimate the impact of these exposure measures on violent organized crime and on presidential election outcomes, with particular attention to support for left-wing populism.

We begin by reporting the differential effects of domestic and foreign robot adoption on employment and exports, following Faber (2020). Foreign automation reduces wages and lowers exports to highly automated U.S. industries such as automobiles, while domestic automation is associated with increased production. More importantly, our main contribution concerns political outcomes. Consistent with our theoretical expectations, regions more exposed to foreign robot adoption experience higher levels of narcocrime, homicides, and other indicators of violent organized crime, as well as greater support for populist-left presidential candidates. These effects are not driven by domestic robot adoption. Taken together, the findings show how technological change in advanced economies is transmitted across borders, impacting economic and political outcomes.

This paper makes three contributions. First, we provide, to our knowledge, the first systematic evidence that automation in the Global North generates social and political spillovers in the Global South, where access to comparable technology and social protection is limited.[1] Examining exposure to foreign and domestic automation separately, we show that foreign robot adoption in the United States depresses wages and exports in exposed Mexican industries and is associated with higher levels of narcocrime, homicides, and support for populist-left presidential candidates. In doing so, we extend research on the labor-market effects of foreign automation (Artuc et al., 2019; Kugler et al., 2020; Faber, 2020), connect work on automation in advanced economies (e.g., Kurer, 2020; Gallego and Kurer, 2022) with evidence from emerging markets (Giuntella et al., 2024; Hidalgo and Micco, 2024), and engage the political economy of development (Dube and Vargas, 2013; Dube et al., 2016). These outcomes do not mirror those emphasized in the North (e.g., right-wing populism), arguably because weaker welfare states and the presence of organized crime shift the forms of political and social response in the South. Second, we jointly study globalization and automation and show how foreign technological change is transmitted through trade to reallocate employment and reorient politics (e.g., Rodrik, 2018b; Colantone et al., 2021). Finally, our results inform debates on the rise of populism and on demands for compensatory policies (Stokes, 2025; Rettl, 2025) in at least two ways. On the one hand, we extend current work on the relationship between globalization, automation, and electoral backlash from the North to the Global South. On the other hand, we explore directly the roots of the current transformation of electoral markets and behavior in Latin America.

[1] For discussion of welfare states in emerging markets, see Holland (2018); Nooruddin and Rudra (2014); Rudra (2002).

2 The Political Economy of Foreign Automation Shocks

In this section, we first detail how the adoption of foreign robots negatively affects employment and wages in the Global South. We then discuss the social and political consequences of exposure to foreign robot adoption. First, citizens may respond to the resulting labor surplus by exiting the legal local labor market, leading to a rise in illegal activities and the criminality associated with them. Second, voters may be more likely to support left-populist candidates who promise pro-redistribution platforms and the redeployment of state-led industrial policies.

2.1 Foreign Automation and Labor Market Disruption

Among other production technologies, industrial robotics have become a particularly important channel in replacing and augmenting labor, especially for emerging markets embedded in global supply chains.[2] Unlike fixed-purpose machines such as conveyor belts or bottling equipment, industrial robots are programmable, capable of executing a variety of tasks across multiple dimensions, and able to operate with minimal human control. Empirical studies of the impact of domestic automation in advanced economies find that industrial robots, often associated with higher productivity, also come with lower employment and wages (Acemoglu and Restrepo, 2020).[3]

The evidence from emerging economies is more limited and mixed. Brambilla et al. (2022) find that domestic robot adoption leads to greater unemployment and informality in Argentina, Brazil, and Mexico.[4] Similarly, Giuntella et al. (2022) show that robot adoption

[2]For a discussion of labor substitution and augmentation, see, for instance, Acemoglu and Restrepo (2019); Acemoglu et al. (2024).

[3]Domestic robot adoption in advanced economies is also linked to a smaller share of work by unskilled labor (Graetz and Michaels, 2018), reductions in manufacturing employment (Dauth et al., 2021), declines in local employment (Chiacchio et al., 2018), and greater wage disparity between high- and low-skilled workers (Humlum, 2019).

[4]The informal sector as a buffer is a distinct characteristic of developing and emerging markets, relative

in China is linked to a substantial decline in labor force participation and wages, especially among low-skilled workers. By contrast, Faber (2020) estimates a positive effect of domestic robot adoption on labor market outcomes in Mexico, likely due to the boost in exports.

However, domestic robot adoption is not the only, or even the primary, source of technological exposure for the Global South; instead, foreign robot adoption may be. For example, according to the 2024 World Robotics Report, Mexico and Brazil operate 55,849 and 20,491 robots, respectively, compared to 381,964 in the United States. Put differently, Mexico has about 59 robots per 10,000 workers, while the U.S. has 295. These disparities mean that workers in emerging economies, part of global production chains, are competing not only with Northern workers, but also with Northern robots for offshorable tasks.

To characterize the economic consequences of foreign automation, we rely on the tasks framework of production (e.g. Acemoglu and Autor, 2011; Grossman and Rossi-Hansberg, 2008). In this framework, the production of a good or service is broken into tasks, each of which can be performed by different inputs: domestic labor, foreign labor, or capital such as machines and software. Firms allocate tasks across inputs according to comparative advantage, balancing relative costs and technological capabilities. Offshoring allows firms in the Global North to assign labor-intensive tasks to cheaper foreign workers, though doing so entails additional transaction and coordination costs. In equilibrium, inputs are allocated to tasks according to their comparative advantage. When the cost of automation falls, firms shift some tasks away from both domestic and foreign labor and toward capital. Data from the IFR indicate that these costs have fallen sharply, with average robot prices declining by roughly 80 percent between 1995 and 2017—from above USD 130,000 to under USD 27,000—making this form of capital far more accessible as a substitute for labor.[5] An increase in trade barriers or wages of foreign labor can also lead to a decrease in the cost of automation relative to foreign labor.

to the advanced economies.

[5] Construction Physics, January 2024. See also IFR, World Robotics Report.

Although the framework is typically applied to the distributional consequences of automation for labor within advanced economies, it also has important implications for the division of work between North and South. Offshoring generates employment opportunities when Northern firms shift tasks abroad, but these opportunities are vulnerable to automation shocks in the North. As Northern robot adoption reduces the incentives to offshore, emerging economies face risks of "reshoring" and weakened trade linkages (Feenstra and Hanson, 1999a; De Backer et al., 2016). Firms' decline in demand for labor in the Global South could emerge through several channels. First, firms may reshore production, defined narrowly as the relocation of a plant from the South to the North. Second, firms could slowdown offshoring by reducing their demand for inputs from the Global South that were previously supplied via exports to the Global North (e.g. related party and arms-length trade). Another slowdown of offshoring would be the decline in new foreign investment (where new projects no longer occur at the same level). We thus use "reshoring" broadly to imply a reduction in demand for tasks performed in the emerging market. Together these constitute a negative labor market shock, although we are not able to distinguish between them at this time.[6]

Following Acemoglu and Restrepo (2020) and the extension by Faber (2020), we conceptualize the impact of the foreign robot shock in emerging markets as the balance of two competing forces: displacement and productivity effects. On the one hand, when the cost advantage of Global South labor declines, producing in the Global North becomes more profitable. As noted above, this can occur through an increase in the relative cost of using labor in the South or a decline in the relative cost of automation in the North. Displacement occurs when the adoption of labor-replacing capital in the Global North reduces the demand for tasks performed by foreign labor as the set of tasks performed by robots expands. This can negatively impact workers who are directly displaced and the labor market more generally. On the other hand, the productivity effect occurs when automation increases the efficiency of firms in the Global North, thus increasing their demand for imports of non-automated

[6] One could imagine that a factory closure or major layoffs are more salient than a gradual decline.

tasks from the Global South. Employment in the latter might be preserved or even grow as firms in the Global North expand production and are better able to bear the costs of offshoring. Thus, automation can boost trade by improving productivity, which may lead to an increase in imports from the Global South.

Recent empirical work documents the impact of automation on labor and trade. An analysis of U.S. robot adoption on Mexican labor markets by Artuc et al. (2019) shows that each additional robot per thousand U.S. workers reduces the growth rate of Mexican exports per worker by 6.7% (p.16). Similarly, Faber (2020) find negative effects of U.S. robot adoption on both exports from and employment in Mexico. In a meta-analysis of 24 studies, Pinheiro et al. (2023) conclude that automation in the Global North facilitates reshoring, implying adverse consequences for Global South labor markets. Focusing on developed economies, Hidalgo and Micco (2024) demonstrate that rising ICT penetration disproportionately reduces imports from sectors with high routine-task intensity, lowering the average annual import growth rate between 1995 and 2018. Meanwhile, Artuc et al. (2023) find that although an increase in robot density in Northern countries is associated with an increase in imports from developing countries, there is a greater increase in exports to developing countries, leading to an overall decline in net sectoral imports from the Global South.Finally, in a firm-level analysis, Stapleton and Webb (2020) show that firms that offshored before automating reduced their share of imports from lower-wage countries, while those that automated first subsequently became more likely to import from lower-wage countries. Taken together, these studies suggest that while automation reshapes trade patterns in complex ways, the dominant trend is a reduced demand for labor-intensive imports from developing countries.

In the short- to medium-term, we expect labor demand in exposed economies to fall because labor markets in the Global South often operate with surplus labor. This not only limits the ability of low-skilled workers to benefit from globalization (Rudra, 2005), but it also makes negative shocks harder to absorb. Displaced workers are unlikely to move into comparable industries. Instead, they tend to shift into agriculture, services, or extractive activities, which generally offer lower earnings and weaker protections than factory work. Recent evidence highlights such compositional changes, showing that foreign automation raises demand for raw materials like mining outputs (Stemmler, 2023) rather than manufactured goods. We therefore expect negative labor market effects–including reduced employment, lower wages, and greater reliance on the informal sector–to be most pronounced in communities more exposed to foreign robot adoption through global production linkages.

These dynamics underscore the importance of distinguishing between domestic and foreign robot adoption when evaluating labor market outcomes. In the emerging market context, the distributional effects of domestic robot adoption may diverge from exposure to foreign robot adoption, because the balance of the labor-replacing and productivity-enhancing effects differs.

2.2 From Labor Market Shock to Criminal Activity

The first outcome that we look at is criminal activity. There is a rich theoretical and empirical literature in economics linking adverse labor market shocks to rises in violence and illicit activity. This is particularly likely to be true where institutions are weak. The intuition follows a classic opportunity-cost logic: when legitimate employment opportunities shrink and incomes fall, the relative appeal of criminal endeavors increases (Becker, 1968). In such moments, people who lose their livelihoods may turn to illicit activities as an alternative source of income. Numerous studies confirm this pattern. In Colombia, the collapse of coffee prices in the late 1990s depressed farm earnings and fueled civil violence in coffee-growing regions (Dube and Vargas, 2013). Similarly, in rural Mexico, falling maize prices pushed farmers toward drug cultivation, enabling cartels to expand and violence to rise (Dube et al., 2016). Environmental shocks have similar effects: droughts and crop failures, proxied by declines in vegetation, raised homicide rates in Mexican municipalities as residents turned to the narcotics trade (Cavazos Hernandez and Sivakumar, 2022). Across these cases, the mechanism is consistent—when legal incomes dry up, illicit work becomes a more attractive option.

This logic also applies to negative labor market shocks from globalization. Exposure to trade liberalization and import competition can devastate local industries and spark social instability.[7] In Brazil, regions more exposed to steep tariff cuts in the 1990s saw sharp increases in crime, with 75–93% of the rise attributed to worsening employment prospects and weakened public services (Dix-Carneiro et al., 2018). Similar patterns emerge in Mexico, where China's entry into global manufacturing led to factory closures, layoffs, and a surge in drug trafficking and violent crime (Dell et al., 2019). According to Dell et al., organized criminal networks reduced the "entry costs" for displaced workers to shift into illicit activities, increasing drug-related homicide in areas that have drug trafficking organizations present. The cartels may also respond by shifting activity to labor markets with more slack and lower wages because labor costs are the most significant component of their costs. In short, global market shocks are able to fuel crime by eroding the economic foundations of legitimate work.

We argue that automation abroad generates a negative shock to labor demand, producing effects on crime similar to other economic disruptions. When advanced economies adopt robots and labor-saving technologies, demand for exports and outsourcing from developing regions declines, leading to job losses and wage reductions. Displaced workers not only face shrinking opportunities locally, but they also have fewer options to relocate. In wealthier countries, migration often acts as a safety valve after labor shocks. For example, U.S. regions heavily exposed to industrial robots saw substantial out-migration and population decline

[7] Of course, positive shocks, like the expansion of markets through exports can have the opposite effect. For instance, Erickson and Owen (2025) find that export opportunities benefiting avocados was associated with a decline in cartel violence in Mexico.

(Faber et al., 2022). In contrast, for workers in developing economies, these responses may be limited—especially when traditional destinations are also automating or imposing stricter immigration controls.

This creates a situation where workers are effectively trapped in deteriorating local economies. Under such conditions, informal or illicit activity may become one of the few remaining avenues for survival. Where criminal networks are present, they can exploit the surplus of jobless individuals. The abundance of unemployed labor lowers the opportunity cost of joining these groups and raises willingness to take risks, ultimately fueling both recruitment and violence. Thus, we expect that foreign robot adoption will lead to higher levels of violence and organized crime in the communities most exposed to it. We hypothesize that

Hypothesis 1 (Organized crime) *Communities with greater exposure to foreign-robot adoption will experience increased levels of violence and organized crime.*

Finally, it is important to clarify the mechanism we propose. We argue that the link between economic dislocation and violent crime is driven by direct economic incentives—displaced workers turning to the underground economy—rather than by psychological distress or social breakdown. This stands in contrast to the "deaths of despair" perspective, which ties automation to declining mental health, substance abuse, suicide, or petty crime (e.g., Liang et al., 2025a). In our account, rising violence under automation shocks reflects a rational, if illicit, adjustment: as formal employment vanishes, individuals and organizations redirect labor into informal and criminal markets. In this way, automation-induced stress is less about despair-driven self-destruction than about structural pressures that expand organized crime and strengthen its influence in affected regions.

2.3 Political response: Left populism

Adverse labor market shocks also have significant consequences at the ballot box. In much of the Global North, economic shocks from automation and globalization have reshaped politics by fueling support for right-wing populism. The displacement of middle-income, middle-skill workers and the limited response of mainstream left parties created space for populist entrepreneurs who capitalized on anti-globalization and especially anti-immigration sentiment. Studies of the United States and Europe show that exposure to robots (Anelli et al., 2019, 2021; Caselli et al., 2021; Frey et al., 2018; Gonzalez-Rostani, 2025; Milner, 2021) and imports (Margalit, 2011; Jensen et al., 2017; Autor et al., 2020; Che et al., 2022; Colantone and Stanig, 2018; Milner, 2021) shifted many working-class voters to the right. Riding on the support of anti-globalization and anti-immigration voters, populist parties succeeded in reshaping an electoral map that had been frozen since the Cold War (Boix, 2019).

The political consequences of foreign robot adoption in the Global South are likely to take a different form. In contrast to advanced economies, relatively low-skilled workers—from the perspective of advanced economies—in labor-abundant economies (like Mexico), benefiting from the initial process of globalization (Rogowski, 1989), have been found to support free trade in the Global South (Menéndez González et al., 2023), at least initially (Rudra et al., 2021). Although workers who once benefited from economic integration may not turn against globalization per se, those in locations negatively impacted by the process of reshoring toward northern economies may increasingly favor state intervention and redistribution to manage the costs.

This is likely to entail a fall in the electoral strength of any parties that had implemented an economic liberalization agenda since the 1980s. As in the North, disaffected voters warmed up to populist-nationalist solutions that rejected the so-called Washington consensus and an international order favoring macroeconomic stability and globalization. Still, whereas northern electorates supported right-wing populist parties, Global South voters have often leaned toward left-wing populist forces.[8] The Global South shift toward leftist populism, which emphasizes, among other things, beefing up the regulatory state, a more muscular industrial policy around state-owned companies, and higher mandated minimum wages (Edwards, 2019), probably responded to three reasons: the supply of political ideas, the dynamics of migration, and the structure of the welfare state.

First, in the Global North, where mainstream center-left and center-right parties agreed on the benefits of globalization and the market economy, populist candidates often grew after grafting themselves to (small) far-right parties and focusing on an anti-immigration platform. By contrast, Latin American politics had been traditionally organized around an economically liberal (electorally weak) right and a broad, left-leaning populist movement (Dornbusch and Edwards, 1990). The collapse of import-substituting industrialization (ISI) policies and the introduction of structural adjustment programs weakened the latter, temporarily leading an important part of the Latin American Left to embrace the pro-market and moderate pro-redistribution stances of European social democracy (Cleary, 2006; Baker and Greene, 2011; Roberts, 2015). A spike in income inequality, increased unemployment, and the spread of informal jobs resulted in growing voter disillusionment with market reforms driven by the Washington consensus regime (Roberts, 2007; Garay, 2023). Riding on growing popular malaise about "neoliberalism" and globalization, the old Left made a political comeback in several countries (Baker and Greene, 2011; Feierherd et al., 2023; Aksoy et al., 2024), offering what Sebastian Edwards has referred to as a "new populism" program (Edwards, 2019).

Second, as net exporters of labor, the restrictive immigration policies espoused by Global North populists made no sense in Global South countries. Instead, protectionist politics

[8]Some European voters have also switched to left-wing populist parties. Interestingly, they do in those more "peripheral" regions, that is, those regions that, from an economic point of view, are somewhat closer to middle-income economies: Greece, parts of Spain, and eastern Germany.

turned around the terms of foreign investment and the potential relocation of multinationals, and, therefore, about the potential need for industrial statism. Populist leaders like Hugo Chávez (Venezuela), Evo Morales (Bolivia), and Andrés Manuel López Obrador (Mexico) explicitly addressed popular discontent by criticizing neoliberalism, privatizations, and foreign influence. In countries most affected by neoliberal reforms, populist candidates, promising redistribution and greater social protection, gained support from voters hurt by market policies and frustrated with right-wing governments (Murillo et al., 2010; Wiesehomeier and Doyle, 2013).

Finally, operating within weak-capacity states, yet concerned about income distribution and poverty alleviation, populist politicians pushed for an expansion of targeted, needs-based programs, legally enforced wage rises, and sector-specific price controls. These policies emerged as traditional labor-based party systems weakened due to declining union membership and widening divisions between formal-sector insiders and precarious informal workers (Garay, 2023).

Overall, our expectation is that a decline in labor market conditions should lead to a leftward shift in citizens' political preferences, as voters increasingly demand pro-worker policies such as social protection, job guarantees, and redistribution.[9] In the particular political context we examine, given the supply of parties, this shift should strengthen left populist candidates. In short:

Hypothesis 2 (Left populism) *Communities with greater exposure to foreign-robot adoption will be more likely to support left-populist political parties.*

One might wonder whether this is about support for populism, the left, or left-populism

[9] In the Brazilian context, Cavalcante et al. (2023) finds that more exports are associated with support for the right, given less demand for redistribution. At the same time, Rettl (2025) finds that a decline in exports led to a decline in support for PT as citizens shifted their demand for redistribution away from the state and towards evangelical churches.

specifically. First, right-wing populists are also present in Latin America, including Bolsonaro in Brazil and José Antonio Kast in Chile, and beyond. Like their counterparts in the Global North, these leaders combine elements of nationalism, majoritarian identity politics, and social conservatism. Their economic programs frequently remain neoliberal or pro-market, which aligns them more with business elites rather than with workers experiencing economic dislocation. This contrasts with left-wing populists in Latin America, who traditionally mobilize disaffected workers through redistributive agendas and anti-elite rhetoric directed at domestic and foreign capital. Support for right-wing populists in emerging markets, therefore, tends to emerge in contexts where cultural cleavages overlap with economic grievances, or where corruption and incompetence have delegitimized the left, as in Brazil under the Workers' Party (Hunter and Power, 2019).

With respect to the question of whether support for AMLO (and Morena more generally) represents support for the left or a left populist, we argue that AMLO/Morena represents the latter. A distinctive feature of populists in the Global South is their emphasis on law and order and anti-corruption as core platforms, often in response to high crime rates or discredited political establishments. While AMLO campaigned on leftist economic issues, he was not liberal on social/cultural issues. He also highlighted corruption and violence as key issues that his government would address. Thus, like other (right) populists in the region, he focused on law and order and corruption. We discuss the scope conditions further in the conclusion.

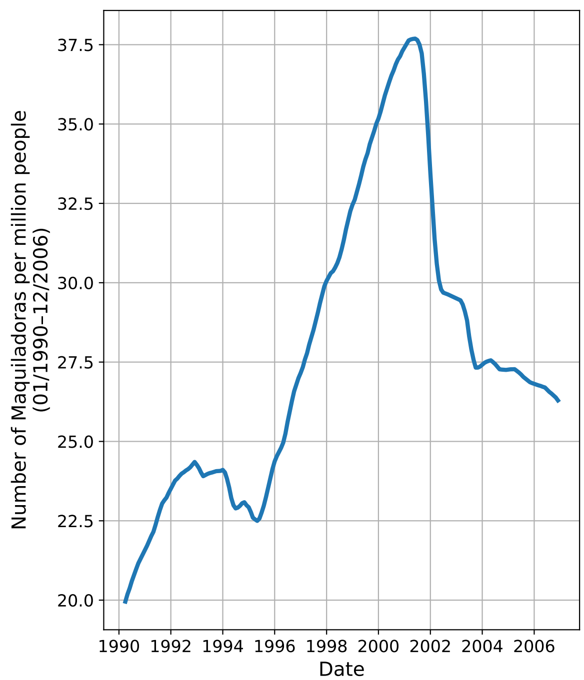
3 Background: The Mexican Context

Mexico provides a compelling case to analyze how automation in advanced economies impacts developing countries. Its deep economic integration with the United States, longstanding migration connections, and entrenched organized crime networks uniquely position Mexico to illustrate the broader implications of automation-induced labor market shifts. The economic interdependence is particularly pronounced: in 2024, 83% of Mexico's exports went to the U.S. (López and Vázquez, 2025), constituting approximately 15% of total U.S. imports (Mann, 2024). Key sectors such as automotive manufacturing, which have rapidly embraced automation in the U.S., represent significant sources of employment in numerous Mexican regions, rendering them especially susceptible to structural changes abroad.

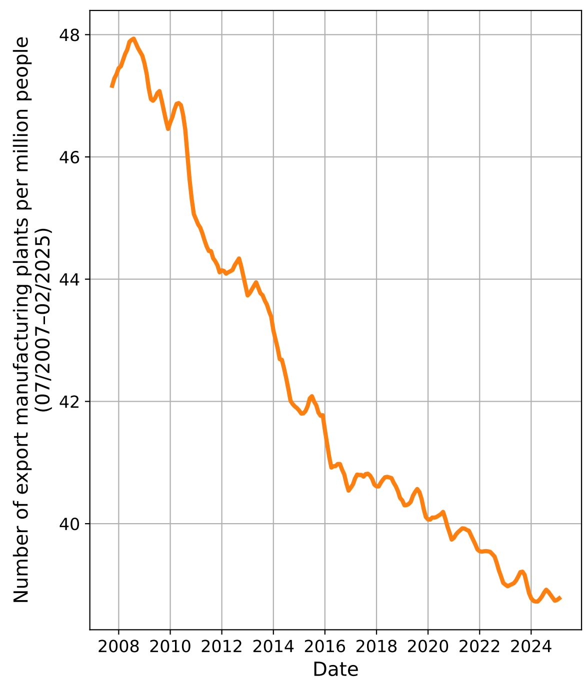
The acceleration of automation in advanced economies has reduced the demand for low-skilled labor, curtailed offshoring activities (Artuc et al., 2019; Acemoglu and Restrepo, 2020; Faber, 2020), and thus exposed Mexico to substantial economic vulnerabilities. Crucially, the prevalent influence of criminal organizations within Mexico exacerbates the political and social consequences of economic shocks. Cartels have historically exploited economic downturns and institutional weaknesses, intensifying violence, especially during electoral periods, to assert territorial dominance (Dube et al., 2013; Trejo and Ley, 2021). Thus, Mexico's integration into global trade, combined with volatile security dynamics, offers a particularly insightful context for studying the transnational impacts of technological disruptions.

Figure 1 illustrates the evolving landscape of export-oriented manufacturing plants in Mexico from 1990 to 2025. Because of the decision in 2007 by Mexico's National Institute of Statistics to include non-Maquiladora export facilities, the left plot reports 4-month moving averages of maquiladoras from 1990 to 2006, and the right graph displays export manufacturing plants per million inhabitants from 2007 to 2025. Following the enactment of NAFTA in 1994, there was a substantial rise in export manufacturing establishments. However, since the mid-2000s, coinciding with the rapid adoption of robotics in the U.S., a marked decline in the number of these plants per capita has occurred, potentially reflecting the displacement of human labor by automation technologies capable of assembling intermediate goods into finished products.

Complementing this, Figure 2a and Figure 2b depict parallel increases in industrial robotics



(a) Maquiladoras per million people (Jan 1990–Dec 2006).

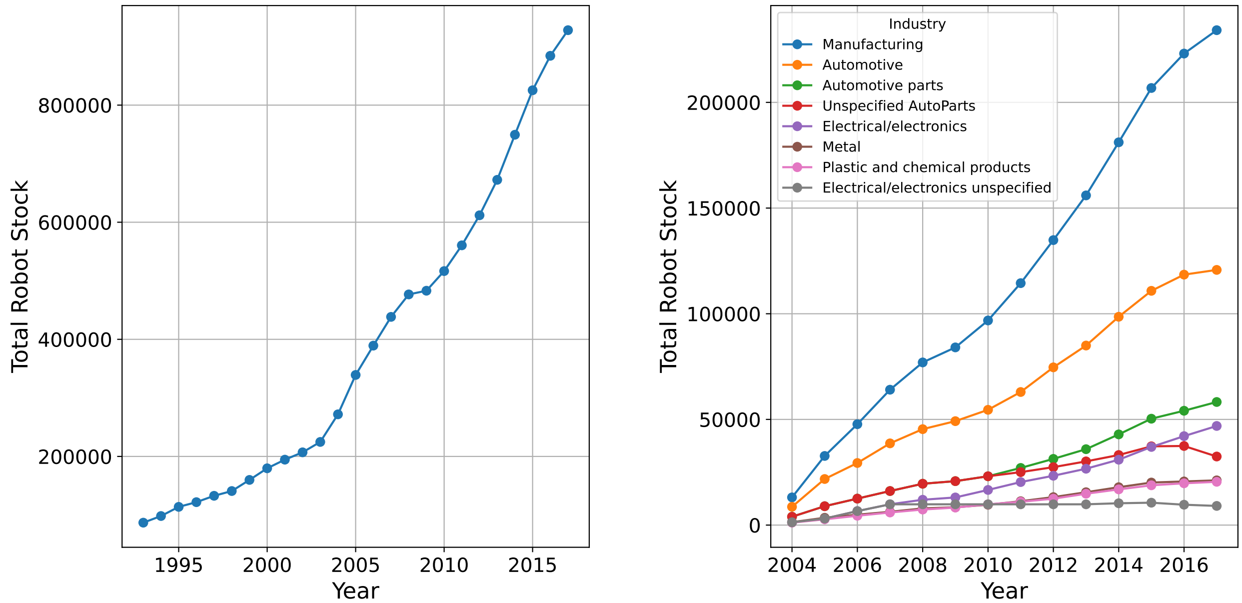


(b) Export manufacturing plants per million people (Jul 2007–Feb 2025).

Figure 1: 4-month moving average number of maquiladoras and number of export manufacturing plants.

Note: This figure plots the 4-month moving averages of maquiladoras (Jan 1990–Dec 2006) and export manufacturing plants (Jul 2007–Feb 2025) per million inhabitants in Mexico. The break around early 2007 arises from a methodological update in INEGI's EMIME and IMMEX series when non-Maquiladora export facilities were first included. Authors' own elaboration based on data from INEGI.

in the United States, particularly within key sectors like automotive, machinery, and electronics, which align closely with Mexico's export profile. The temporal alignment of rising automation and reshoring events is notable: since the mid-2010s, over 200 reshoring incidents have been documented (see Appendix A.1), providing empirical support for automation's influence in reshoring decisions. Data from the Reshoring Initiative (Reshoring-Initiative, 2025) highlights automotive production as the most frequently reshored activity, followed by machinery and electronics—sectors among the most aggressive adopters of automation in the U.S (see Figure A.2). Furthermore, automation emerges as a primary motivation cited by companies for returning production to the U.S. (see Figure A.4). These documented reshoring cases illustrate extreme manifestations; it is likely that subtler adjustments—such as reducing imports of intermediate goods rather than fully relocating production—are even



(a) Industrial Robots (1993–2017).

(b) Industrial Robots by industry (2004–2017).

Figure 2: Stock of Industrial Robots in the United States.

Note: This figure plots robot stock trends by industry in the United States, focusing on the eight industries with the highest total robot stocks from 2004 onwards. Industry-level disaggregated data is available starting from 2004. Authors' own elaboration based on data from the International Federation of Robotics (IFR), 1993–2017.

more widespread. Overall, these dynamics underscore Mexico's value as a case study for understanding how global automation trends, within the context of fragmented global production, can have substantial political and economic consequences for developing countries.

In terms of political background, Mexico's Institutional Revolutionary Party (PRI), which had governed uninterruptedly for over seven decades, implemented a package of pro-market economic reforms in the late twentieth century. Over the subsequent two decades, the center-right National Action Party (PAN), which took over the Mexican government in 2000, and PRI, which regained the Mexican presidency twelve years later, converged around a technocratic, market-oriented consensus. Growing violence and the erosion of the rule of law, caused by the rise of organized crime and its infiltration of electoral and local institutions, compounded by tepid economic growth in real terms and growing concerns over income inequality, triggered significant public disenchantment with both parties (Trejo and Ley, 2021; Gutiérrez-Romero and Iturbe, 2024; Gutiérrez-Romero and UNU-WIDER, 2025). The declining support for the Mexican political establishment then culminated in the decisive 2018 electoral victory of Andrés Manuel López Obrador (AMLO) and his National Regeneration Movement (MORENA), which promised to restore the fast economic growth of the 1960s and 1970s (Castro Cornejo, 2023).

Against this backdrop, MORENA leaders consistently cast their project as pro-worker. AMLO often praised technological progress while warning of "jobless growth." For example, after inaugurating a highly automated distribution center in 2020, describing it as "puro robot," he stressed that, in a country with high demand for work, public spending and private investment must also generate employment for ordinary people.[10] Similarly, he has repeatedly contrasted capital-intensive facilities with labor-intensive public works such as roads, rail, and energy projects, and tied worker protection to economic sovereignty by criticizing offshoring and abusive outsourcing. MORENA's agenda included restricting subcontracting in 2021,[11] raising the minimum wage, creating the northern border *Zona Libre*, and launching projects like the Tren Maya and the Dos Bocas refinery. In AMLO's Sixth Government Report, he declared that his administration sought to halt "antipopular, entreguista y corrupta" policies, with 'entreguista' referring to the ceding of national resources to foreign interests (e.g, US) and domestic elites.[12] Complementing this agenda, social programs such as *Jóvenes Construyendo el Futuro* and *Sembrando Vida* were framed as support for those left behind by economic change. The political payoff was evident in places like Coahuila, a northern state dependent on steel and auto manufacturing, where thousands of layoffs during 2019–2020 were followed by Morena's electoral gains in 2021 and 2024. Federal promises of intervention—including Sheinbaum's pledge to revive the steel industry—resonated with displaced workers. As one steelworker put it, government involvement "calms the situation and lifts the spirits of the more than 8,000 former workers."[13]

[10] Inauguración del Camino Rural a Santiago Nejapilla. December 11, 2020.

[11] April 2021.

[12] "promover leyes para frenar la política antipopular, entreguista y corrupta que se había impuesto y legalizado por el predominio de un poder oligárquico con apariencia de democracia," September, 2024.

[13] April, 2025.

4 Empirical Strategy

Our empirical strategy builds on the methodologies proposed by Acemoglu and Restrepo (2020) and Faber (2020), distinguishing between domestic and foreign exposure to robot adoption. The standard approach to measuring exposure to domestic robot adoption, following Acemoglu and Restrepo (2020), is defined as:

$$\text{Exposure to domestic robots}_{c(t_0,t_1)} = \sum_{i \in I} \ell_{ci,1990} \left(\frac{R^{MX}_{i,t_1} - R^{MX}_{i,t_0}}{L_{i,1990}} \right)$$

Here, R^{MX}_{i,t_1} and R^{MX}_{i,t_0} represent the number of robots in industry i in Mexico at times t_1 and t_0, respectively. $\ell_{ci,1990}$ is the share of employment in industry i relative to total employment in region c in 1990, while $L_{i,1990}$ denotes the industry's total employment at that time. Using employment shares from 1990 minimizes endogeneity concerns related to recent economic conditions or policy decisions. Our main variable of interest is foreign robot exposure, which extends the domestic measure by shifting attention to automation in trading partners, particularly the United States, following Faber (2020). To better capture external shocks, this measure also incorporates industry-level offshorability.

$$\text{Exposure to foreign robots}_{c(t_0,t_1)} = \sum_{i \in I} \ell^{f}_{ci,1990} \left(\frac{(R^{US}_{i,t_1} - R^{US}_{i,t_0}) \cdot O_{i,1992}}{L^{f}_{i,1990}} \right)$$

Here, R^{US}_{i,t_1} and R^{US}_{i,t_0} indicate the estimated number of robots in industry i in the U.S. at times t_1 and t_0, respectively. $\ell^{f}_{ci,1990}$ represents the share of export-producing employment in industry i relative to total employment in commuting zone c in 1990, and $L^{f}_{i,1990}$ is total employment in foreign industry i. The offshorability factor $O_{i,1992}$ captures the initial reliance of U.S. industries on Mexican imports as inputs, calculated as:

$O_{i,1992} = \frac{I^{MXUS}_{i,1992}}{Y^{US}_{i,1992}}$

In this formula, $I^{MXUS}_{i,1992}$ is the proportion of U.S. industry i's inputs imported from Mexico, while $Y^{US}_{i,1992}$ is the total output of U.S. industry i. This measure thus quantifies each industry's vulnerability to automation shocks based on its dependence on Mexican-produced inputs.

Finally, we address potential endogeneity arising from the correlation between robot adoption and unobserved factors affecting local labor markets by employing an instrumental variable approach, using the increase in robots in the rest of the world as an instrument for foreign exposure (and we do the same for domestic exposure). Our main independent variable is then:

$$\text{External exposure to foreign robots}_{c(t_0,t_1)} \equiv \sum_{i \in I} \ell^{f}_{ci,1990} \left(\frac{\left(R^{WLD}_{i,t_1} - R^{WLD}_{i,t_0}\right) \hat{O}_{i,1990}}{L^{f}_{i,1990}} \right)$$

The superscript WLD denotes the sum over European countries that are also incorporating technology (i.e, excluding the US and Mexico) for which industry-level data are available from 1993 onward.[14] To address potential endogeneity in our initial offshoring to Mexico proxy, we follow Feenstra and Hanson (1999b) and Faber (2020) in defining it as the share of imported intermediate inputs from the same industry over total non-energy intermediates in U.S. industry i in 1990 (across all source countries).

The equation we estimate is as follows:

[14] These countries include Denmark, Finland, France, Germany, Italy, Norway, Spain, Sweden, and the United Kingdom.

$$y_{POST} = \alpha + \beta^f \text{Exp. to foreign robots}_{c(t_0,t_1)} + \beta^d \text{Exp. to domestic robots}_{c(t_0,t_1)} + \mathbf{X}_{c,t_0}\gamma + \delta_t + \varepsilon_{c(t_0,t_1)}$$

where the dependent variable is one of our three outcomes (incidence of violent crime or left party vote share) measured in the final period of our sample. The main independent variable is foreign robot exposure. Since domestic adoption may also have significant social and political effects, we include it as well. The equation controls for the influence of other relevant covariates ($\mathbf{X}_{c,t_0}$), time-period fixed effects (δ_t), and other regional characteristics (e.g., city-specific trends). The unit of analysis is Mexican local labor markets (i.e., commuting zones, CZs). CZs are clusters of municipalities that feature strong commuting ties within, and weak commuting ties across CZs.

In the main text, we present results for the level of the dependent variable post-shock, because of limitations on the availability of different outcome variables during the early period. However, in the appendix, as we discuss further below, we present the results for the first differences specifications, where possible, given data constraints.

5 Data

In this section, we describe our main data sources. We note that our independent and control variables are drawn from Faber (2020)'s replication data. We combine the latter with data on our outcome variables.

Independent Variable: Exposure to Robots The independent variable in our analysis is exposure to foreign robots, which is sourced from Faber (2020). This measure comes from combining Census data, trade data, and robot data from the International Federation of

Robotics (IFR). The IFR has collected data on the shipments and operational stocks of industrial robots by country and industry since 1993. These robots are defined as reprogrammable, multipurpose manipulators used in various industrial automation tasks, including manufacturing, agriculture, and utilities (IFR, 2015). Because the IFR data are available only at the country–industry–year level, it is not possible to identify which U.S. robots directly affected which Mexican regions. Instead, prior research allocates exposure across commuting zones (CZs) based on their pre-shock industry employment structure, updated with subsequent adoption either abroad or at home (Faber, 2020; Acemoglu and Restrepo, 2020). Both foreign and domestic exposure are thus measured using a Bartik-style approach, which leverages the initial industrial composition of each CZ and the number of robots adopted by industry. This captures how employment concentration shapes local exposure rather than relying on direct robot installations within each CZ.[15]

Exposure to foreign robots is not only linked to technology adoption in trade partners but also incorporates offshorability. This is captured by dividing the value of Mexican imports to the US in each industry (sourced from the UN Comtrade database) by the total output of the corresponding US industry (from the US Bureau of Labor Statistics) in 1992. In this external exposure measure, the offshoring indicator for US industries, $O_{i,1990}$, represents the share of imported intermediate goods in each industry relative to total non-energy intermediates within the US industry in 1990. This measure, inspired by the outsourcing index of Feenstra and Hanson (1999b), typically used for the 4-digit SIC72 classification, is adjusted to the broader IFR industry classification. Faber (2020) mapped each SIC72 industry to an IFR industry and calculated the employment-weighted average for each IFR industry, using employment data from the County Business Patterns (CBP) dataset.

In Figure 3, we show commuting-zone-level exposure to domestic (blue) and foreign (red)

[15]Since most firms produce for both domestic and foreign markets, isolating export-related employment is challenging. However, Maquiladoras are primarily export-oriented; for example, they accounted for nearly half of Mexico's exports in 2005, making them a reliable proxy. Thus, export-producing employment ($\ell^{f}_{ci,1990}$) is measured using Maquiladora employment data from the non-digitized CEPAL (1994) report.

robots across Mexico between 2000 and 2015. Exposure to foreign robots, highlighted in red, is largely concentrated in the northern region, reflecting nearshoring dynamics and proximity to U.S. manufacturing centers. Cities with high foreign robot exposure include Ciudad Juárez, Tijuana, Monterrey, and Reynosa. In contrast, exposure to domestic robots, depicted in blue, shows a more balanced distribution across the country, with substantial robotization observed in central areas including Mexico City, Guadalajara, León, and other industrial hubs. This pattern underscores a broader integration of domestic automation compared to the geographically concentrated foreign robot exposure in northern industrial zones.

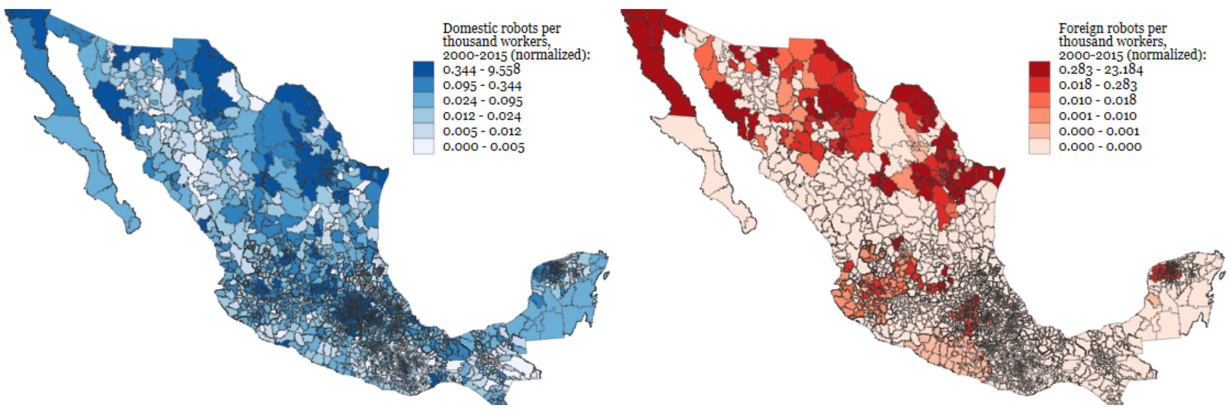


Figure 3: Commuting zone-level variation in exposure to domestic and foreign robots, 2000–2015.

Dependent Variables For the dependent variables in this analysis——crime and vote share——we use data from various sources. The data were initially collected at the municipality level and subsequently aggregated at the commuting zones (CZ) level using a crosswalk between municipalities and CZs.

Violent crime. Data on organized crime and homicides come from multiple sources. From CONAPO and the Mexican National Institute of Statistics and Geography (INEGI), we use the 2018 homicide rate, defined as the number of homicides per 10,000 inhabitants at the municipal level. To capture variation across types of crime, we also use detailed municipal-level data from the Center for Research and National Security (CISEN) in 2016. These data allow us to isolate narcocrime and compute the incidence of organized crime per 10,000 inhabitants in each CZ.

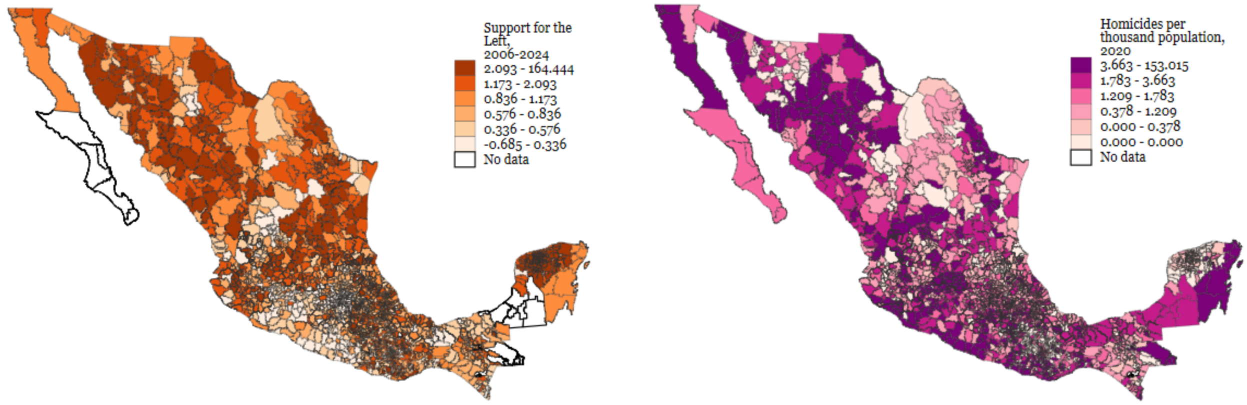
Since official statistics do not consistently distinguish drug-related killings, overall homicide rates are often used as a proxy for narcocrime, following prior work (BenYishay and Pearlman, 2013; Dell, 2015; Cavazos Hernandez and Sivakumar, 2022). As a complementary measure, we employ the organized-crime index developed by Osorio and Beltran (2020), which uses natural language processing techniques to detect references to organized crime in news reports. This proxy is available annually for 2000–2018, providing a longer time series to validate our findings. See Figure 4b for variation in homicide incidence.

Electoral outcomes. To study the political effects of foreign robot adoption, we focus on support for left-wing parties, measured by the vote share of Morena. Our primary analysis focuses on the post-shock elections of 2018 and 2024. We also explore trends across the full period from 2006 to 2024, as well as outcomes for other party families (center, right, and null votes).[16] Electoral data are drawn from the Instituto Nacional Electoral (INE) database.[17] See Figure 4a for variation in Left support.

Control Variables Several characteristics of the CZ may affect our outcome variables. Drawing on Faber's replication data, we control for several additional factors that may shape our outcomes of interest. The first is the share of workers in occupations usually classified as routine tasks. This measure is derived from occupation-level data and a crosswalk with the US case (Autor, 2013). We control for this in 1990 as a measure of vulnerability to

[16]Morena was officially registered in 2014. For first difference analysis, we treat AMLO's earlier vote share a proxy for Morena.

[17]https://prep2024.ine.mx/publicacion/nacional/base-datos



(a) Left support. (b) Homicides per thousand people in 2020.

Figure 4: Commuting zone-level variation in key dependent variables.
Notes: The maps represent the variation in homicides per thousand people in 2020, and the variation in support for the Left from 2006 to 2024. Refer to Figure A.7 for a map illustrating the variation in organized crime between 2000 and 2018.

automation prior to the shock.

Two additional variables related to the economic context are also included. First, NAFTA exposure captures the effects of the North American Free Trade Agreement, which came into effect in 1994, and altered industry-level tariffs for many sectors. The measure reflects each commuting zone's exposure to NAFTA by interacting its initial employment shares with the tariff reductions brought about by the agreement. It is proxied by $\sum_{i \in I} \ell_{ci,1990} \Delta\tau_i$, where $\ell_{ci,1990}$ represents the share of employment in industry i out of total CZ employment in 1990, and $\Delta\tau_i$ represents the NAFTA-induced tariff change in industry i.

Second, exposure to Chinese import competition is included to account for the impact of increased Chinese imports to both Mexico and the US. This control accounts for changes in Mexican imports from China as well as the indirect competition in foreign markets, using a Bartik-style measure that incorporates industry-specific changes in Chinese imports to both countries. It is defined as:

$$\text{Exp. to Chinese import competition}_{c(t_0,t_1)} = \sum_{i \in I} \ell_{ci,t_0} \left[\frac{I^{CNMX}_{i,t_1} - I^{CNMX}_{i,t_0} + O_{i,t_0} \left(I^{CNUS}_{i,t_1} - I^{CNUS}_{i,t_0} \right)}{L_{i,t_0}} \right]$$

where I^{CNMX}_{i,t_1} and I^{CNMX}_{i,t_0} represent the value of imports from China to Mexico in industry

i at times t_1 and t_0, respectively, and I_{i,t_1}^{CNUS} and I_{i,t_0}^{CNUS} represent the same for imports to the US. L_{i,t_0} is the total employment in industry i at time t_0, and O_{i,t_0} is the initial share of imported intermediate goods in US industry i.

In addition to these economic and occupational-level variables, we include demographic characteristics of each CZ. Specifically, we consider pre-shock characteristics such as the share of men and the share of people with primary education as their highest level of education in 1990. We also include industry employment shares in manufacturing and the share of employment relative to the population in 1990. Moreover, we incorporate dynamic variables, such as the changes in the employment-to-population ratio between 2000 and 2015 (the same period during which robot exposure changed). Finally, we include fixed effects for eight broad regions in Mexico.

6 Results

In this section, we present the results of our analyses. Before moving to the main results for crime and presidential vote share, we present evidence that foreign automation influences local employment outcomes and export performance as outlined in our theory. We estimate a specification parallel to our main specifications of interest using Faber (2020)'s data. Figure 5 presents coefficient estimates of the effects of exposure to domestic and foreign automation on employment across various demographic groups (left panel) and exports across distinct industry sectors (right panel). These results document that exposure to foreign robot adoption is linked to lower employment and a reduction in exports, especially in sectors like electronics, electrical machinery, and automotives. This is important to demonstrate because our theory rests on the assumption that exposure to foreign robots has negative labor market outcomes. We present this here, but also refer interested readers to the extensive analysis in Faber's piece.

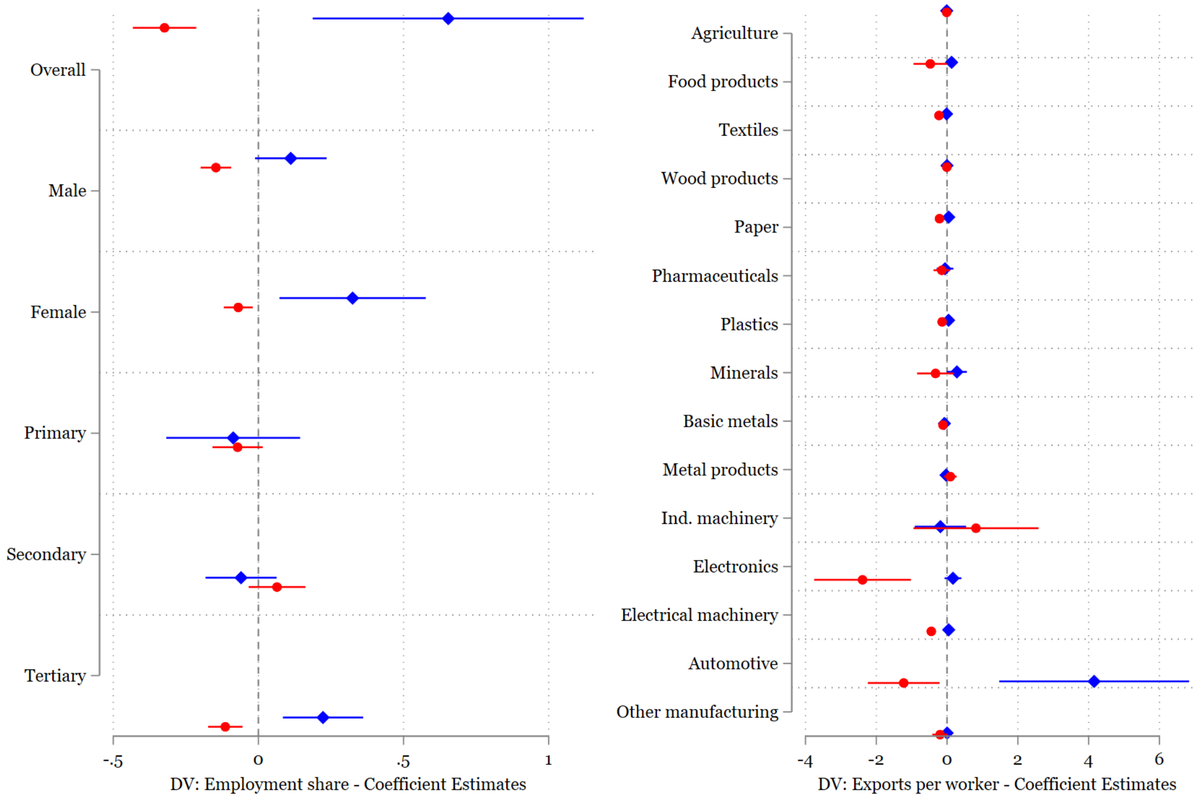


Figure 5: Changes in employment (left panel) and exports (right panel) in relation to exposure to domestic and foreign robots, 2000–2015. Blue coefficients indicate exposure to domestic robots; red coefficients indicate exposure to foreign robots.

Notes: The dependent variables related to employment measure changes in employment levels between 2000 and 2015, either overall, by gender, or by education level. The dependent variable related to exports captures exports per worker by industry between 2004 and 2014. All specifications include the following control variables: (1) Region: fixed effects for eight broad regions in Mexico; (2) Demographics: 1990 commuting zone (CZ) characteristics, including the share of men and the share of individuals whose highest level of education is primary; and (3) Industry: the share of employment in manufacturing in 1990 and the 1990 employment-to-population ratio. All regressions are weighted by each CZ's share of the national working-age population in 1990. Standard errors are robust to heteroskedasticity and clustered at the state level.

We focus on the effects on overall employment, where exposure to foreign automation is associated with negative employment outcomes, as clearly indicated by the aggregated *Overall* coefficient, whereas domestic automation appears to increase employment. These patterns hold for male and female employment.

An industry-specific examination of exports underscores substantial sectoral variation in susceptibility to foreign automation. The automotive sector notably benefits from enhanced domestic technology integration, demonstrating increased export capacity. In contrast, exposure to foreign robots significantly reduces exports in sectors such as automobiles, food products, and electronics. These outcomes highlight a critical mechanism: increased technological adoption in the US reduces demand for Mexican-produced inputs, adversely impacting export-dependent sectors.

These structural shifts in employment and export patterns provide insights into the socio-political dynamics discussed previously. Employment displacement and export decline triggered by foreign automation intensify local economic distress, fostering social and political responses such as increased violence (e.g., increased homicide rates) or growing support for pro-worker political platforms.

6.1 Effect of Foreign Robots on Organized Crime

We first consider involvement in organized crime, an outcome that is particularly relevant to the Global South. Table 1 reports the results consistent with our **Hypothesis 1**. Column 2, for example, shows that exposure to foreign robots is positively correlated with the number of homicides. We observe similar effects for other crime categories, such as narcocrime and human trafficking (columns 4 and 5).

A one standard deviation increase in foreign robot exposure results in an increase of 0.25 homicides per 10,000 population, equating to a 4.33 pp increase relative to the standard deviation of the homicide rate. For narcocrime, a one standard deviation increase in foreign robots corresponds to a 28% increase in the rate of narcocrimes per 10,000 population, relative to the SD of narcocrime rates. We also find consistent evidence when examining changes in organized crime from 2000 to 2018 using the measure developed by Osorio and Beltran (2020), which employs NLP techniques to detect news reports about organized crime. This measure similarly reveals a pattern of increased organized crime linked to greater foreign robot exposure. See Table A.4.

Table 1: Impact of exposure to robots on violence.

OLS	(1) Crimes	(2) Homicides	(3) Kidnapping	(4) Narco	(5) Human Traffic
External exposure to domestic robots	-7.017**	-0.781**	-0.0107	-0.792	0.00185
	(3.353)	(0.322)	(0.0189)	(0.559)	(0.00616)
External exposure to foreign robots	0.747	0.211**	0.0100**	0.592**	0.00336**
	(0.718)	(0.100)	(0.00388)	(0.285)	(0.00155)
Demographics	✓	✓	✓	✓	✓
Industry	✓	✓	✓	✓	✓
Region	✓	✓	✓	✓	✓
Observations	1802	1802	1802	1802	1802
R^2	0.166	0.197	0.130	0.455	0.127
IV	(1) Crimes	(2) Homicides	(3) Kidnapping	(4) Narco	(5) Human Traffic
Exposure to domestic robots	-6.638**	-0.734**	-0.00981	-0.733	0.00187
	(3.103)	(0.297)	(0.0175)	(0.543)	(0.00580)
Exposure to foreign robots	0.833	0.234**	0.0111***	0.654*	0.00369**
	(0.769)	(0.114)	(0.00397)	(0.336)	(0.00184)
Demographics	✓	✓	✓	✓	✓
Industry	✓	✓	✓	✓	✓
Region	✓	✓	✓	✓	✓
Observations	1802	1802	1802	1802	1802
R^2	0.170	0.203	0.132	0.409	0.122
F	12.09	9.267	21.68	6.305	15.00
Kleibergen-Paap Wald F-stat	172.7	172.7	172.7	172.7	172.7

Notes: The dependent variable in column 1 refers to the homicide rate, while column 2 refers to the number of homicides per 10,000 population, both sourced from CONAPO. Column 3 refers to the number of narcocrimes per 10,000 population, sourced from CISEN. All specifications include the following control variables: 1) Region: fixed effects for eight broad regions in Mexico; 2) Demographics: 1990 CZ demographics, including the share of men and the share of people with primary education as their highest level; 3) Industry: shares of employment in manufacturing in 1990 and the 1990 level of employment-to-population ratio. All regressions are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to heteroskedasticity and clustered by state. The coefficients marked with $***$, $**$, and $*$ are significant at the 1%, 5%, and 10% confidence levels, respectively. Refer to the full Tables in Appendix A.2-A.3. Refer to Table A.4 for results examining changes in organized crime between 2000 and 2018.

Substantively, the positive relationship between foreign robot exposure and both homicides and narcocrime suggests that technological advancements abroad, particularly in countries like the US, can undermine offshoring and reduce economic opportunities in developing countries. As foreign firms adopt automation and reorganize supply chains, the resulting decline in demand for exports disrupts local industries, deepens poverty, and leaves some individuals with fewer alternatives beyond participation in illegal activities or organized crime.

In settings such as Mexico—where organized criminal groups already maintain a strong presence and operate within weak or contested state institutions—these economic shocks do more than generate incidental violence. They create strategic openings for criminal organizations to expand their ranks, consolidate territorial control, and leverage violence to influence politics. This aligns with previous research demonstrating that criminal organizations frequently serve as alternative sources of employment during economic downturns (Dube and Vargas, 2013; Dube et al., 2016). Such dynamics have significant political implications, as economically-driven expansions of organized crime enable groups to leverage violence, influence electoral outcomes, capture local governments, and renegotiate territorial control (Dube et al., 2013; Trejo and Ley, 2018, 2021). Moreover, strengthened criminal organizations become more capable of forging agreements with politicians or targeting opposition candidates to secure favorable governance arrangements (Hernández Huerta, 2020).

Economic vs. Death of Despair. Our argument emphasizes a structural, economically rational explanation for the relationship between automation and crime. In contexts characterized by job displacement and constrained labor mobility, individuals experience a reduction in the opportunity cost of engaging in illicit activities. This economic mechanism contrasts with the findings of (Liang et al., 2025b) for the United States, which link automation-driven increases in crime primarily to psychological factors—specifically mental health deterioration and "deaths of despair"—rather than to direct economic incentives. Supporting our economic rationale, Tables A.6 and A.7 show no significant relationship between exposure to foreign robots and crimes typically associated with despair-driven motivations, such as property crimes or sexual offenses.[18]

[18] Notably, while automation in advanced economies has generally been associated with increased crime rates, we observe the opposite for domestic robot adoption in our analysis. Specifically, the coefficient for domestic robot adoption is either negative and statistically significant or indistinguishable from zero.

6.2 The Effect of Foreign Robots on Populist Backlash

We now examine whether exposure to foreign automation translates into measurable political shifts. Table 2 presents OLS and IV estimates of the impact of foreign robot exposure on voting shares for the left-populist coalition—MORENA and its 2024 presidential candidate, Claudia Sheinbaum—across commuting zones. Column 1 demonstrates a positive and statistically significant relationship between foreign robot exposure and support for left-wing populism, indicating that regions more exposed to automation abroad systematically exhibited greater backing for MORENA in 2024. Our preferred IV model, which addresses potential endogeneity by treating foreign automation as an exogenous shock, similarly shows a significant increase in MORENA's vote share. Conversely, columns 2 and 3 illustrate a decline in support for right (PAN) and center (PRI) parties, traditionally associated with the political establishment (Castro Cornejo, 2023). There is no effect of the share of null votes. Re-estimating the model as a first difference, to assess changes in Left populist support, yields consistent findings (as shown in Table A.12).

Substantively, these results indicate greater support for the left-wing populist (anti-establishment) candidate in communities highly exposed to foreign automation compared to otherwise similar but less affected communities. This provides evidence supporting our **Hypothesis 2**, which argues that economic disruptions from foreign automation heighten the demand for redistributionist and economically nationalist policies in affected regions.

We look at the 2024 election in our primary analysis because, for the 2018 election, won by AMLO, we cannot rule out with aggregate data that the pattern could, in part, be explained by anti-incumbent economic voting. In Table A.10 and Table A.11, we find similar results when pooling the 2018 and 2024 elections and looking at support for AMLO.

These findings carry important political implications, demonstrating that foreign automation operates as an external economic shock capable of triggering populist backlash. In

Table 2: Effect of Robot Exposure on Electoral Outcomes in 2024 elections

OLS	(1) Sheinbaum (Left)	(2) Galvez (Right)	(3) Alvarez (Center)	(4) Null
External exposure to domestic robots	0.0194	-0.0166	-0.00280	0.000837
	(0.0119)	(0.0131)	(0.00443)	(0.000602)
External exposure to foreign robots	0.00721**	-0.00452	-0.00267*	0.000172
	(0.00274)	(0.00283)	(0.00151)	(0.000191)
Demographics	✓	✓	✓	✓
Industry	✓	✓	✓	✓
Region	✓	✓	✓	✓
Observations	1800	1800	1800	1800
R^2	0.537	0.422	0.292	0.328

IV	(1) Sheinbaum (Left)	(2) Galvez (Right)	(3) Alvarez (Center)	(4) Null
Exposure to domestic robots	0.0186*	-0.0159	-0.00274	0.000801
	(0.0106)	(0.0120)	(0.00414)	(0.000559)
Exposure to foreign robots	0.00792***	-0.00495*	-0.00294*	0.000189
	(0.00277)	(0.00297)	(0.00160)	(0.000202)
Demographics	✓	✓	✓	✓
Industry	✓	✓	✓	✓
Region	✓	✓	✓	✓
Observations	1800	1800	1800	1800
R^2	0.546	0.429	0.293	0.328
F	45.39	49.80	16.95	17.32
Kleibergen-Paap Wald F-stat	172.7	172.7	172.7	172.7

Notes: The dependent variables in columns 1–3 represent each candidate's share of valid votes. Column 4 reports the share of null votes relative to the total number of votes cast. All specifications include the following control variables: 1) Region: fixed effects for eight broad regions in Mexico; 2) Demographics: 1990 CZ demographics, including the share of men and the share of people with primary education as their highest level; 3) Industry: shares of employment in manufacturing in 1990 and the 1990 level of employment-to-population ratio. All regressions are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to heteroskedasticity and clustered by state. The coefficients marked with $***$, $**$, and $*$ are significant at the 1%, 5%, and 10% confidence levels, respectively. Refer to the full Tables in Appendix A.8-A.9. Refer to Table A.12 and Table A.13 for results examining changes between the 2006 and 2024 elections.

Mexico's context, this backlash notably manifested as left-wing populism. Regions heavily impacted by robot-driven job losses rallied behind MORENA, a party advocating substantial redistribution and stronger governmental economic intervention. This aligns with historical patterns in Latin America, where left-wing populist movements have successfully challenged globalization and expanded the state's economic role (Edwards, 2010). MORENA effectively capitalized on these sentiments, emphasizing neoliberal failures, promoting economic sovereignty, and pledging enhanced social safety nets and support for domestic industries.

While automation-induced disruptions often fuel right-wing populism and nationalist sentiment in Western Europe and the United States (Anelli et al., 2021; Frey et al., 2017;

Gonzalez-Rostani, 2025), the presence of a credible left-populist alternative in Mexico channeled workers' grievances toward the political left. Our findings demonstrate that the ideological direction of populist responses to economic shocks varies contextually, particularly leaning leftward in middle-income democracies with viable left-populist movements. Regardless of ideological orientation, distributive politics remain central in addressing the demands of economically vulnerable groups as evidenced by previous work on the US (Gonzalez-Rostani, 2025). MORENA directly appealed to these voters through commitments to cash transfers, expanded social programs, increased minimum wages, improved pensions, and investments in domestic infrastructure. Additionally, economic nationalism featured prominently, as MORENA blamed previous administrations and international economic pressures for local hardships. Claudia Sheinbaum, aligned with President López Obrador, emphasized nationalist policies, advocating Mexico's energy sovereignty, criticizing unfavorable trade agreements, and aiming to reclaim strategic sectors—positions that resonated deeply with voters adversely affected by international competition.

Alienation as a Political Mechanism. A possible pathway linking foreign automation to populist support is through political alienation and demobilization. We explore this by examining regional variation in labor strike activity using INEGI's Huelgas Estalladas dataset, which records the universe of actual strikes ("huelgas estalladas") at national, state, and municipal levels. From these data, we construct annual strike counts by region. As shown in Table A.14, strike activity declines in regions more exposed to foreign robots. Rather than spurring labor militancy, automation-related shocks coincided with fewer strikes. This suggests that foreign automation demobilized labor may have reduced workers' bargaining power and fostered their political alienation rather than collective mobilization—conditions consistent with anti-elitist sentiment and subsequent support for populism.

This interpretation aligns with earlier work on technological disruption and political disengagement. Boix (2019) highlights how technological change has historically coincided with rising mistrust, abstention, and detachment from mainstream politics. Similarly, Gonzalez-Rostani (2024a) shows at the individual level that workers exposed to automation in Europe are less likely to vote, protest, or feel partisan attachment. Agnolin et al. (2025) documents that industrial robot adoption contributes to union decline across European countries, weakening a key channel of labor representation. And Liu and Zhang (2023) argues that fear of automation and offshoring can deepen conflicts between workers, employers, and the state, sometimes incentivizing firms to replace workers with robots. Taken together, these findings support the view that foreign automation may erode collective action and trust in unions, leaving workers disconnected from traditional political mobilization. In such contexts, alienation itself becomes fertile ground for populist appeal, as economically insecure voters gravitate toward anti-establishment leaders who claim to speak for the "forgotten." In Mexico, the combination of declining strikes and rising support for Morena is consistent with this dynamic: economic disruption encouraged withdrawal from institutionalized labor politics while fueling a populist backlash.

7 Conclusions

Our analysis shows that the social and political effects of technological change extend across borders. Robot adoption in advanced economies depresses labor demand in developing countries, with far-reaching consequences for society. In Mexico, exposure to U.S. robotization is substantial: between 1993 and 2015, roughly 234,000 industrial robots were installed in the United States, and each corresponds to a loss of slightly more than one job in Mexico (Faber, 2020). Using regional exposure measures and an instrumental variable strategy, we find that areas more exposed to foreign automation experience higher levels of violent organized crime and greater electoral support for left-wing populist candidates. These effects are robust to accounting for domestic automation and other shocks. In short, when firms in the North automate, communities in the South absorb the costs—through job loss, heightened insecurity, and political realignment.

These findings advance several debates. For globalization and development, they identify a new channel through which integration produces uneven outcomes. While trade and offshoring once promised employment and growth in developing economies, technological advances abroad can erode those gains by undercutting low-wage comparative advantage. Theories of globalization must therefore account for technological shocks alongside import competition and financial crises.

Second, our work speaks to the literature on automation and political behavior. Studies of automation's domestic impacts in advanced democracies have linked worker displacement to voter discontent, often manifesting in the rise of radical-right or anti-establishment movements (e.g. Frey et al., 2017; Anelli et al., 2021; Gonzalez-Rostani, 2025). Our findings extend this line of inquiry to the developing world, showing that automation-driven job loss can generate a populist backlash in emerging democracies as well, albeit with contextually specific outcomes. In Mexico's case, communities hard-hit by foreign robot adoption gravitated toward left-wing populism, rallying behind candidates who promised redistribution, economic nationalism, and an expanded role for the state. By documenting a left-populist surge in response to automation abroad, our study enriches the comparative understanding of how economic grievances translate into political action.

Third, our results have implications for the study of violence and governance in developing contexts. We show that foreign automation shocks destabilize local security: in Mexican regions facing falling labor demand, organized violent crime rises while non-violent property crime does not. The pattern aligns with theories that criminal organizations exploit economic stress and institutional weakness to consolidate power (Trejo and Ley, 2021; Dube et al., 2013; Hernández Huerta, 2020).

Finally, to what extent do the results of our study generalize to other contexts? While Mexico exemplifies exposure to U.S. automation through North American production networks, analogous dynamics may occur elsewhere. The mechanism linking foreign automation to adverse political and social outcomes is broadly applicable to situations where technological change in advanced economies reduces offshoring, demand for imports, or investment in labor-intensive activities abroad. In such cases, in manufacturing or for instance, business-processing, emerging-market regions integrated into those value chains experience negative employment shocks. These shocks depress local incomes, weaken social stability, and alter political preferences. The exact consequences, however, depend on national context, including the nature of economic integration, state and institutional capacity, and the channels through which discontent is mobilized (such as the supply of parties). Other cases that merit attention could include the potential impacts of AI-automation on India and the Philippines, automation in the EU impacting Poland (though Poland also adopts), or other emerging markets in Southeast Asia.

In conclusion, this study underscores that the political economy of automation is fundamentally global. For policymakers, the clear message is that technological change must be understood as a shared challenge and opportunity. Developing robust strategies to manage automation's ripple effects will be essential to sustaining economic development, social stability, and democratic health in an increasingly interconnected age.

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A Online Appendix

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A.1 Reshoring from Mexico

This section examines cases of reshoring from Mexico to the United States since the mid-2000s, with a particular focus on automation-driven relocations.

The dataset was manually compiled from the *Reshore Now* library.[19] All cases available with associated news articles and basic project descriptions were included (a total of 184 cases of restoring from Mexico to the US). For each reshoring event, we collected information on the company involved, the year of reshoring announcement, the industry sector affected, the stated motivations for reshoring, and additional project details when available. Importantly, we focused exclusively on cases where production was previously located in Mexico and subsequently relocated to the United States.

Figure A.1 presents the number of reshoring cases by year. The data show a notable concentration of reshoring announcements between 2012 and 2014. Figure A.2 depicts the distribution of reshoring cases across industries, with automotive and transportation sectors accounting for the largest share, followed by miscellaneous manufacturing and machinery industries.

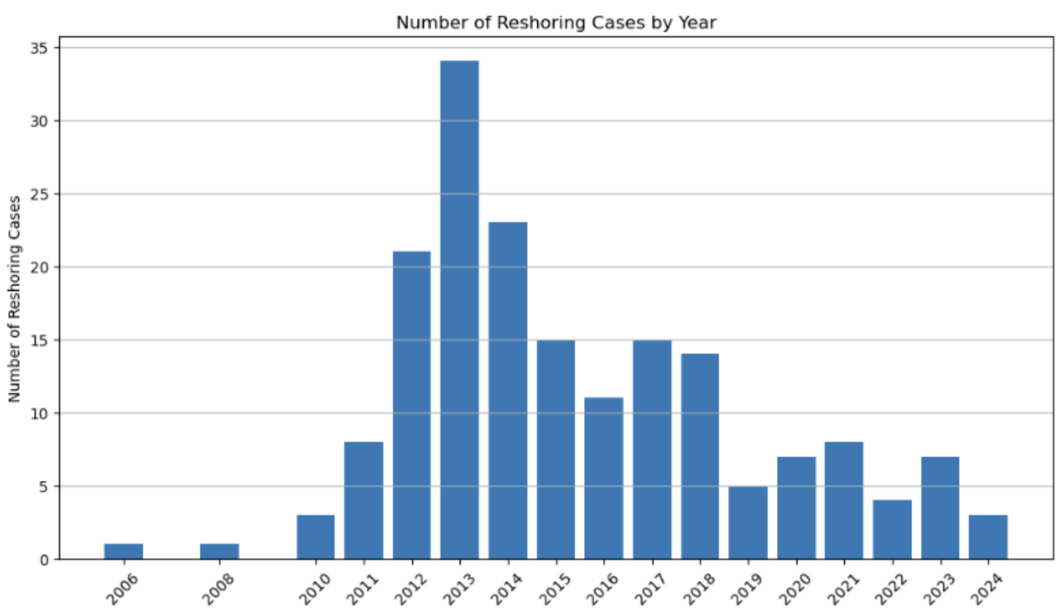

Figure A.1: Number of Reshoring Cases by Year

To better understand the motivations behind reshoring, we conducted a textual analysis of project descriptions. Figure A.3 shows a word cloud summarizing the most frequently cited terms, highlighting incentives, proximity to customers, supply chain improvements, and automation as prominent themes.

Building on this, we employed an unsupervised topic modeling approach (Latent Dirichlet

[19] https://www.reshorenow.org/main-reshoring-library/

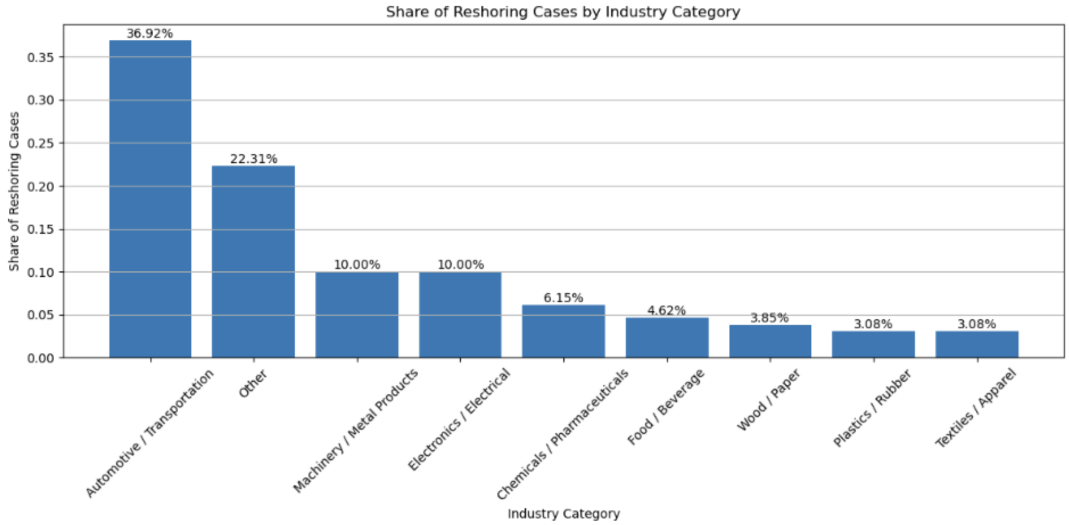

Figure A.2: Share of Reshoring Cases by Industry Category

Allocation, LDA) to classify the main reasons for reshoring. Figure A.4 displays the share of each topic identified through this analysis. The LDA model identified four dominant reshoring rationales, with one of the topics being automation:

- **Brand Image and Wages:** Several companies emphasized concerns related to brand reputation, customer responsiveness, and the control of labor costs. Commonly cited terms include *image*, *brand*, *wages*, and *responsiveness*.
- **Supply Chain and Quality:** Many cases referenced efforts to strengthen logistics, reduce lead times, improve product quality, and enhance supply chain resilience. Keywords associated with this topic include *cost*, *lead*, *market*, *quality*, and *supply chain*.
- **Proximity and Incentives:** Proximity to the U.S. customer base and access to government incentives emerged as crucial drivers in a significant number of cases. Terms such as *proximity*, *incentives*, *government*, and *tax* are central to this topic.
- **Technology and Automation:** A growing share of reshoring is associated with investments in technological capabilities, automation, and manufacturing process innovations. Relevant terms include *technology*, *automation*, *workforce*, and *innovation*.

A.1.1 Reshoring Examples

Figure A.3: Word Cloud of Main Reshoring Reasons

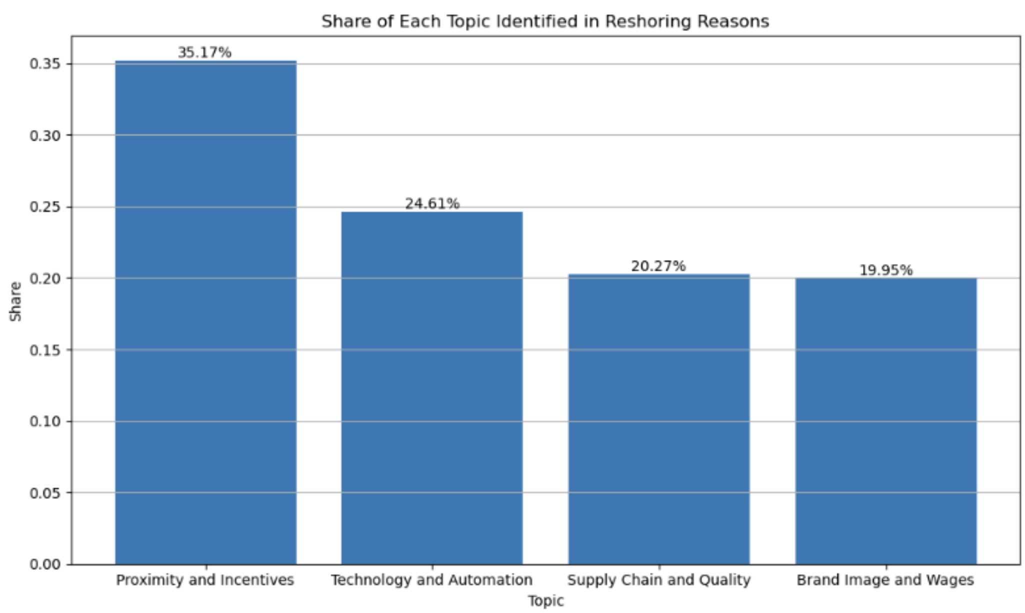

Figure A.4: Share of Each Topic Identified in Reshoring Reasons (LDA Topic Analysis)

Table A.1: Examples of U.S. Companies Reshoring or Canceling Expansion in Mexico due to Technology and Policy Changes

Company	**Event**	**Industry**	**Short Description**	**City**	**Region**	**Source**
Ford Motor Company	Canceled Mexico Plant (Reshoring)	Automotive	Canceled 1.6 billion assembly plant in Mexico; invested 700 million in Michigan for electric/autonomous vehicles.	San Luis Potosí	North-Central	Source
Carrier (UTC)	Canceled Move to Mexico	HVAC Manufacturing	Reversed plans to move Indianapolis furnace plant to Mexico; invested in automation at U.S. factory.	Monterrey (planned)	North	Source
Stanley Black & Decker (Craftsman)	Reshoring to U.S.	Tools Manufacturing	Reshored Craftsman tool production to Texas using robotics instead of expanding abroad.	Multiple (e.g, Hermosillo)	North	Source, Source
EnerSys	Closed Mexico Plant (Reshoring)	Batteries/ Electrical	Closed Monterrey battery facility and shifted production to Kentucky to optimize costs and access U.S. incentives.	Monterrey	North	Source
Samsung Electronics	Reshoring	Home Appliances (Electronics)	Expanded U.S. washer production in South Carolina instead of growing Mexican production.	Querétaro	North-Central	Source
LG Electronics	Considering U.S. Expansion (Cancel Mexico Expansion)	Home Appliances (Electronics)	Considering moving washer and refrigerator production from Monterrey to Tennessee.	Monterrey	North	Source
General Electric (GE Appliances)	Reshoring production to U.S.	Home Appliances	Shifted refrigerator and washer production back to Kentucky from Mexico.	Various	Multiple	Source
Whirlpool Corp.	Reshoring production to U.S.	Home Appliances	Moved commercial washer production from Monterrey, Mexico, to Clyde, Ohio.	Monterrey	North	Source
Horst Engineering	Plant closure and reshoring	Precision Manufacturing	Closed facility in Guaymas, Sonora, moved operations to CT and MA.	Guaymas	Northwest	Source
Caterpillar Inc.	Moved production to U.S.	Heavy Machinery	Transferred truck manufacturing from Escobedo, Nuevo León to Victoria, Texas.	Escobedo	North	Source
General Motors Co.	Supplier reshoring	Automotive	Cut 600 jobs in Mexico by moving parts production to new supplier park in Arlington, Texas.	Silao, Guanajuato	Center	Source

Continued on next page

Table A.1 Continued from previous page

Company	Event	Industry	Short Description	City	Region	Source
Gentex	Reshoring production to U.S.	Motor Vehicle Parts	Closed mirror manufacturing plants in Mexico and China, consolidating production in Zeeland, Michigan, creating 1,600 U.S. jobs.	Not specified	Not specified	Source
Industries	Reshoring production to U.S.	Transportation Equipment	Built new off-road vehicle plant in Huntsville, Alabama, creating 2,000 jobs, partially reversing previous expansion to Monterrey.	Monterrey	North	Source
Otis Elevator (UTC)	Reshoring production to U.S.	Industrial Equipment	Shifted elevator equipment production from Nogales, Mexico, to a modern, automated facility in Florence, South Carolina, consolidating multiple functions previously dispersed internationally.	Nogales	North	Source Source
AmFor Electronics	Reshoring production to U.S.	Electrical Components	Brought wire harness and cable assembly work from suppliers in Mexico and China back to its Portland, Oregon plant to improve delivery, design revisions, and implement lean production techniques.	Not specified	Not specified	Source
Toydozer (Startup)	Reshoring production to U.S.	Toys/Consumer Goods	Shifted plastic toy scoop manufacturing from Mexico to Pendell, Pennsylvania, to reduce costs and address quality issues, leveraging automation and Walmart's Made-in-USA initiative.	Not specified	Not specified	Source
GW Plastics	Reshoring production to U.S.	Medical Manufacturing	Expanded its Tucson, AZ clean-room facility to take over a large medical device assembly program previously done in Mexico, leveraging automated injection molding and packaging capabilities to reduce cost and improve quality.	Querétaro	Central	Source

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Table A.1 Continued from previous page

Company	Event	Industry	Short Description	City	Region	Source
Whirlpool Corp.	Reshoring production to U.S.	Appliances	Shifted production of commercial front-load washing machines from Monterrey, Mexico, to Clyde, Ohio, creating approximately 80–100 U.S. jobs to enhance efficiency and align production with primary markets.	Monterrey	Nuevo León	Source

A.2 Descriptive: Robots

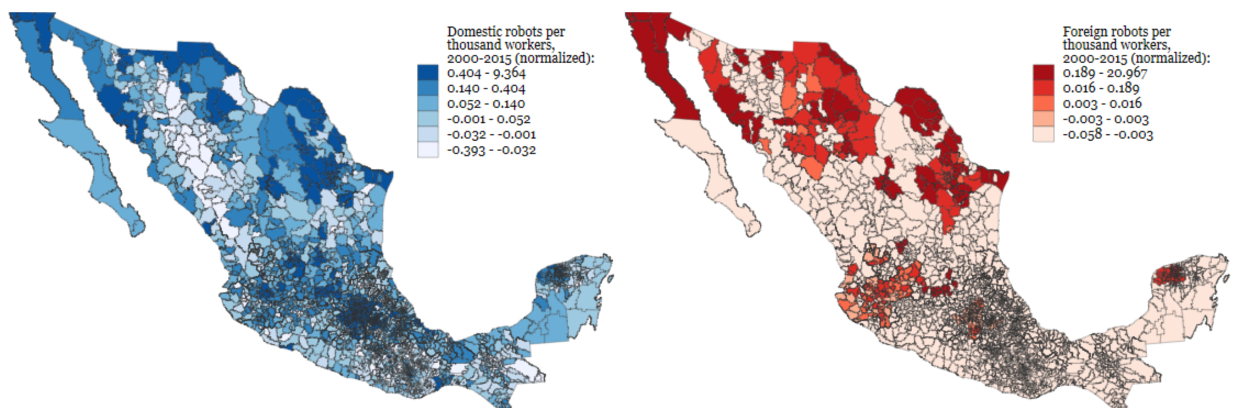

Figure A.5: Commuting zone-level variation in exogenous exposure to domestic and foreign robots, 2000–2015.

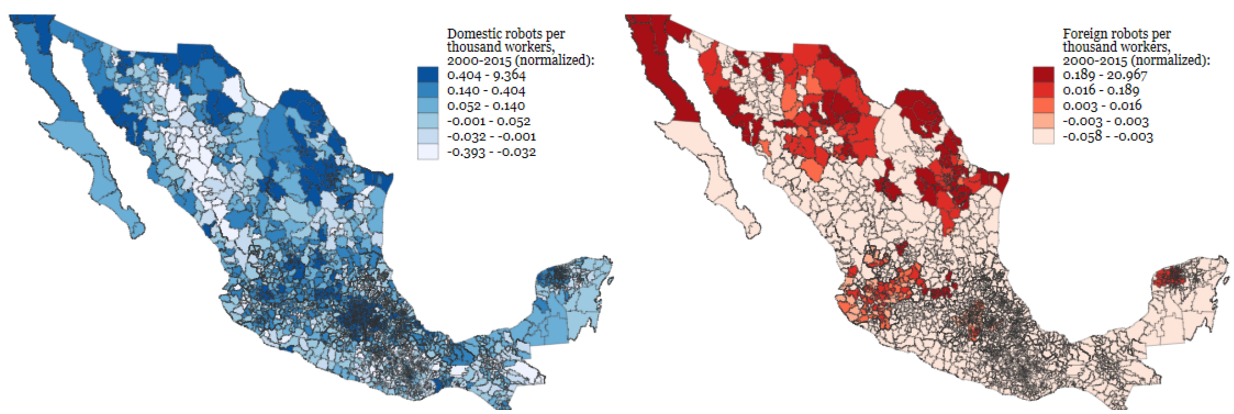

Figure A.6: Commuting zone-level variation in exogenous exposure to domestic and foreign robots, 1993–2015.

A.3 Descriptive: Violence

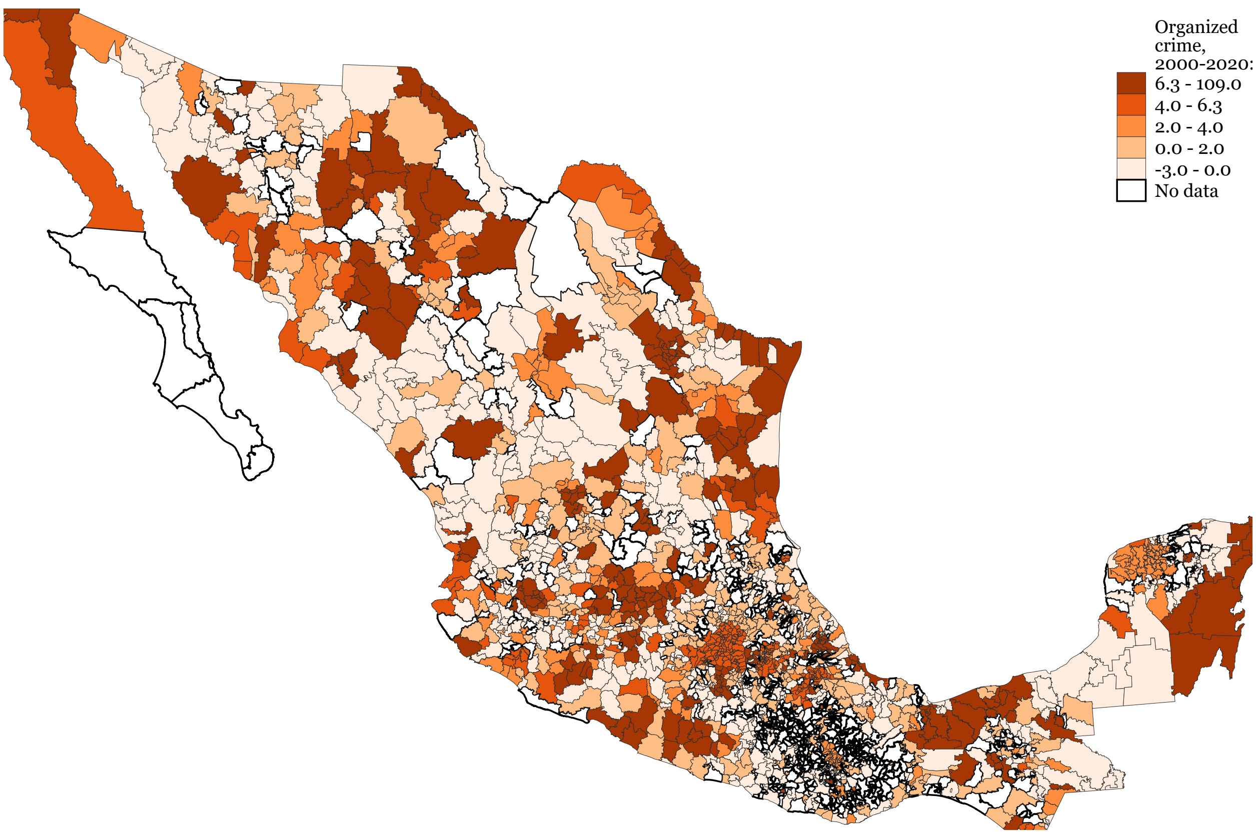

Figure A.7: Commuting zone-level variation in exogenous exposure to domestic and foreign robots, 1993–2015.

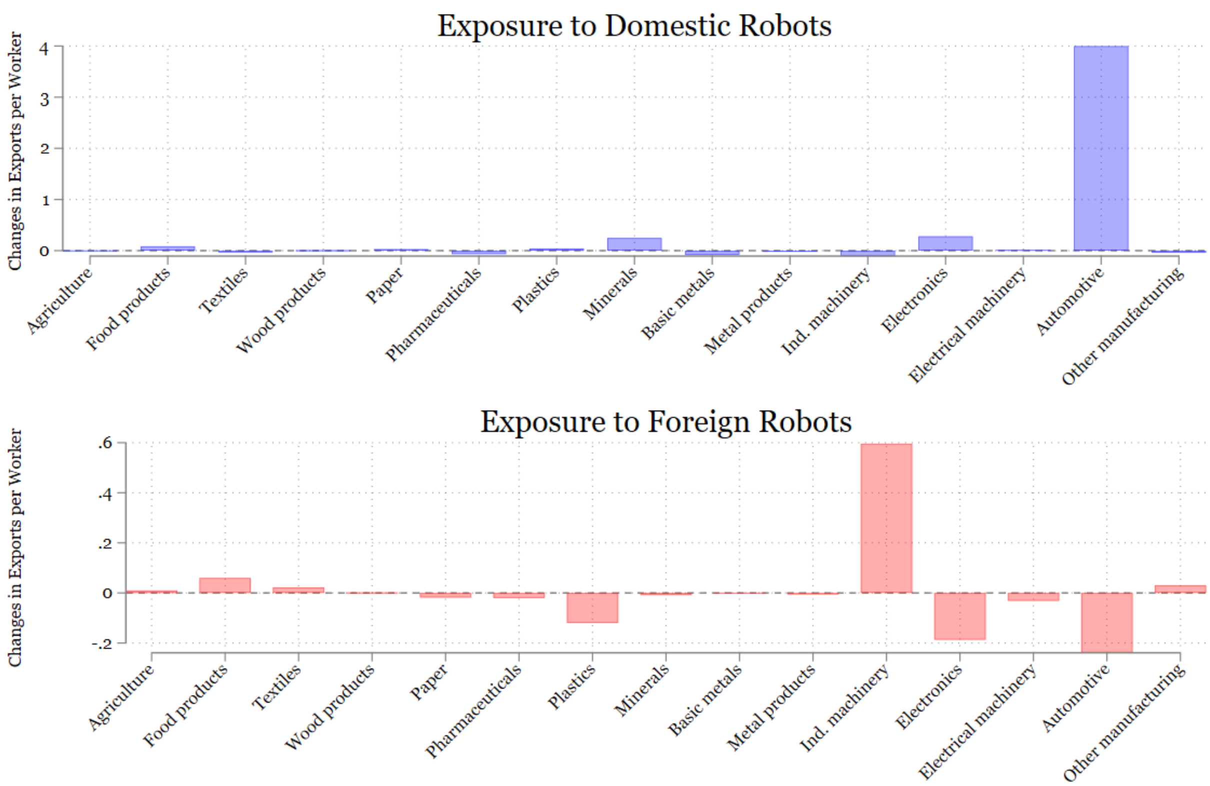

Figure A.8: Changes in exports per worker by industry and their relationship with exposure to domestic and foreign robots, 2000–2015.

A.4 Results: Violence

	(1) Crimes	(2) Homicides	(3) Kidnapping	(4) Narco	(5) Human Traffic
External exposure to domestic robots	-7.017**	-0.781**	-0.0107	-0.792	0.00185
	(3.353)	(0.322)	(0.0189)	(0.559)	(0.00616)
External exposure to foreign robots	0.747	0.211**	0.0100**	0.592**	0.00336**
	(0.718)	(0.100)	(0.00388)	(0.285)	(0.00155)
Share of routine workers in 1990	25.22	-1.203	-0.220	11.57	0.112
	(67.32)	(7.633)	(0.374)	(9.701)	(0.0681)
Exposure to Chinese import competition	0.744	0.135	-0.00376	-0.155	-0.00139
	(1.482)	(0.116)	(0.00465)	(0.188)	(0.00127)
Exposure to tariff changes from NAFTA	290.0	50.15	2.677**	-92.08*	0.902
	(259.8)	(30.44)	(1.264)	(47.31)	(0.661)
Change in employment-to-population ratio 00-15	0.432	0.0414	-0.00140	0.0486	0.000667**
	(0.342)	(0.0354)	(0.00181)	(0.0316)	(0.000285)
Share of men in 1990	25.35	5.305	-0.0305	-2.036	-0.0782
	(177.2)	(21.37)	(0.469)	(17.72)	(0.180)
Share of people with primary education in 1990	1.272	1.205	0.124	3.550	-0.00481
	(23.18)	(2.370)	(0.130)	(3.180)	(0.0550)
Share of manufacturer workers in 1990	-4.299	-0.297	-0.202	3.685	-0.0988*
	(35.94)	(3.470)	(0.243)	(4.730)	(0.0502)
Employment to population 1990	-0.125	-0.0123	-0.00122	0.0775	0.000188
	(0.464)	(0.0480)	(0.00190)	(0.0515)	(0.00107)
Region	✓	✓	✓	✓	✓
Observations	1802	1802	1802	1802	1802
R^2	0.166	0.197	0.130	0.455	0.127

Table A.2: Impact of exposure to robots on Violence (OLS).

Notes: The dependent variable in column 1 refers to the homicide rate, while column 2 refers to the number of homicides per 10,000 population, both sourced from CONAPO. Column 3 refers to the number of narcocrimes per 10,000 population, sourced from CISEN. All specifications include the following control variables: 1) Region: fixed effects for eight broad regions in Mexico; 2) Demographics: 1990 CZ demographics, including the share of men and the share of people with primary education as their highest level; 3) Industry: shares of employment in manufacturing in 1990 and the 1990 level of employment-to-population ratio. All regressions are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to heteroskedasticity and clustered by state. The coefficients marked with $***$, $**$, and $*$ are significant at the 1%, 5%, and 10% confidence levels, respectively.

	(1) Crimes	(2) Homicides	(3) Kidnapping	(4) Narco	(5) Human Traffic
Exposure to domestic robots	-6.638**	-0.734**	-0.00981	-0.733	0.00187
	(3.103)	(0.297)	(0.0175)	(0.543)	(0.00580)
Exposure to foreign robots	0.833	0.234**	0.0111***	0.654*	0.00369**
	(0.769)	(0.114)	(0.00397)	(0.336)	(0.00184)
Share of routine workers in 1990	27.96	-0.976	-0.221	11.57	0.109
	(65.75)	(7.501)	(0.366)	(9.645)	(0.0669)
Exposure to Chinese import competition	0.561	0.0930	-0.00555	-0.262	-0.00194
	(1.525)	(0.116)	(0.00451)	(0.214)	(0.00144)
Exposure to tariff changes from NAFTA	274.7	48.10	2.630**	-95.17**	0.897
	(251.3)	(29.40)	(1.221)	(46.88)	(0.641)
Change in employment-to-population ratio 00-15	0.429	0.0402	-0.00147	0.0447	0.000643**
	(0.336)	(0.0345)	(0.00178)	(0.0325)	(0.000279)
Share of men in 1990	28.12	5.695	-0.0205	-1.397	-0.0766
	(172.8)	(20.88)	(0.462)	(17.87)	(0.178)
Share of people with primary education in 1990	2.012	1.413	0.133	4.130	-0.00154
	(22.91)	(2.351)	(0.125)	(3.232)	(0.0547)
Share of manufacturer workers in 1990	-5.141	-0.234	-0.192	4.208	-0.0942*
	(34.73)	(3.406)	(0.231)	(4.807)	(0.0496)
Employment to population 1990	-0.145	-0.0137	-0.00120	0.0783	0.000214
	(0.456)	(0.0468)	(0.00187)	(0.0515)	(0.00104)
Region	✓	✓	✓	✓	✓
Observations	1802	1802	1802	1802	1802
R^2	0.170	0.203	0.132	0.409	0.122
F	12.09	9.267	21.68	6.305	15.00
Kleibergen-Paap Wald F-stat	172.7	172.7	172.7	172.7	172.7

Table A.3: Impact of exposure to robots on Violence (IV).

Notes: The dependent variable in column 1 refers to the homicide rate, while column 2 refers to the number of homicides per 10,000 population, both sourced from CONAPO. Column 3 refers to the number of narcocrimes per 10,000 population, sourced from CISEN. All specifications include the following control variables: 1) Region: fixed effects for eight broad regions in Mexico; 2) Demographics: 1990 CZ demographics, including the share of men and the share of people with primary education as their highest level; 3) Industry: shares of employment in manufacturing in 1990 and the 1990 level of employment-to-population ratio. All regressions are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to heteroskedasticity and clustered by state. The coefficients marked with $***$, $**$, and $*$ are significant at the 1%, 5%, and 10% confidence levels, respectively.

	(1)	(2)
	Δ Org. Crime	Δ Org. Crime
External exposure to domestic robots	-2.662**	
	(1.251)	
External exposure to foreign robots	2.640***	
	(0.681)	
Exposure to domestic robots		-2.455*
		(1.283)
Exposure to foreign robots		2.924***
		(0.851)
Nafta/China Shock	✓	✓
Demographics	✓	✓
Industry	✓	✓
Region	✓	✓
Observations	1033	1033
R^2	0.460	0.418
F	13.01	8.272
Kleibergen-Paap Wald F-stat		169.2

Table A.4: Impact of exposure to robots on Changes in Organized Crime 2000-2018.

Notes: The dependent variable is the difference in the number of organized crime reported by Osorio and Beltran (2020). All specifications include the following control variables: 1) Region: fixed effects for eight broad regions in Mexico; 2) Demographics: 1990 CZ demographics, including the share of men and the share of people with primary education as their highest level; 3) Industry: shares of employment in manufacturing in 1990 and the 1990 level of employment-to-population ratio. All regressions are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to heteroskedasticity and clustered by state. The coefficients marked with $***$, $**$, and $*$ are significant at the 1%, 5%, and 10% confidence levels, respectively.

	(1) Crimes	(2) Homicides	(3) Kidnapping	(4) Narco	(5) Human Traffic	(6) Δ Org. Crime
Exposure to domestic robots	-6.385**	-0.734***	-0.00717	-0.733	0.000731	-2.798**
	(2.910)	(0.284)	(0.0168)	(0.531)	(0.00605)	(1.246)
Exposure to foreign robots	0.718	0.234*	0.00989***	0.654*	0.00421**	3.082***
	(0.833)	(0.121)	(0.00361)	(0.348)	(0.00183)	(0.826)
Distance to US	-0.0108	-0.0000291	-0.000112	0.00000135	0.0000482	0.0147*
	(0.0222)	(0.00209)	(0.0000835)	(0.00302)	(0.0000548)	(0.00877)
Share of routine workers in 1990	34.05	-0.959	-0.157	11.57	0.0822	49.36**
	(70.73)	(8.062)	(0.373)	(9.586)	(0.0728)	(23.03)
Exposure to Chinese import competition	0.255	0.0922	-0.00875*	-0.262	-0.000570	0.624
	(1.354)	(0.115)	(0.00518)	(0.176)	(0.00167)	(0.827)
Exposure to tariff changes from NAFTA	263.0	48.07	2.508**	-95.17**	0.949	165.1*
	(239.4)	(29.43)	(1.150)	(46.33)	(0.699)	(89.35)
Change in employment-to-population ratio 00-15	0.463	0.0403	-0.00112	0.0447	0.000491	-0.116
	(0.326)	(0.0332)	(0.00173)	(0.0339)	(0.000327)	(0.140)
Share of men in 1990	29.66	5.700	-0.00439	-1.397	-0.0835	-40.75
	(177.4)	(21.05)	(0.459)	(17.97)	(0.177)	(60.58)
Share of people with primary education in 1990	-1.141	1.404	0.100	4.130	0.0126	0.0773
	(25.41)	(2.538)	(0.131)	(3.040)	(0.0432)	(10.44)
Share of manufacturer workers in 1990	-4.576	-0.233	-0.186	4.208	-0.0967*	-9.748
	(34.84)	(3.386)	(0.227)	(4.831)	(0.0515)	(13.61)
Employment to population 1990	-0.144	-0.0137	-0.00119	0.0783	0.000209	-0.187
	(0.448)	(0.0468)	(0.00187)	(0.0514)	(0.00104)	(0.158)
Region	✓	✓	✓	✓	✓	✓
Observations	1802	1802	1802	1802	1802	1033
R^2	0.171	0.203	0.136	0.409	0.127	0.426
F	15.43	9.303	13.01	6.177	11.38	12.34
Kleibergen-Paap Wald F-stat	165.0	165.0	165.0	165.0	165.0	162.0

Table A.5: Impact of exposure to robots on Violence (IV), adding distance to the US as a control variable.

Notes: The dependent variable in column 1 refers to the homicide rate, while column 2 refers to the number of homicides per 10,000 population, both sourced from CONAPO. Column 3 refers to the number of narcocrimes per 10,000 population, sourced from CISEN. All specifications include the following control variables: 1) Region: fixed effects for eight broad regions in Mexico; 2) Demographics: 1990 CZ demographics, including the share of men and the share of people with primary education as their highest level; 3) Industry: shares of employment in manufacturing in 1990 and the 1990 level of employment-to-population ratio. All regressions are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to heteroskedasticity and clustered by state. The coefficients marked with $***$, $**$, and $*$ are significant at the 1%, 5%, and 10% confidence levels, respectively.

A.4.1 Results: Death of Despair?

	(1) Sexual Crime	(2) Family Violence	(3) Property Crimes
Exposure to domestic robots	-0.234	-1.529	0.357
	(0.157)	(1.017)	(1.420)
Exposure to foreign robots	0.00658	-0.0426	-0.113
	(0.0472)	(0.521)	(0.390)
Share of routine workers in 1990	0.845	-10.90	24.14
	(3.346)	(20.54)	(16.15)
Exposure to Chinese import competition	0.161**	1.000***	0.460
	(0.0594)	(0.361)	(0.723)
Exposure to tariff changes from NAFTA	12.20	144.0*	-1.928
	(15.23)	(82.60)	(67.68)
Change in employment-to-population ratio 00-15	-0.00856	-0.000150	0.145*
	(0.0157)	(0.0934)	(0.0794)
Demographics	✓	✓	✓
Industry	✓	✓	✓
Region	✓	✓	✓
Observations	1802	1802	1802
R^2	0.499	0.587	0.522

Table A.6: Impact of exposure to robots on other crimes associated with the Death of Despair hypothesis (OLS).

Notes: The dependent variable in column 1 refers to the homicide rate, while column 2 refers to the number of these types of crimes per 10,000 population, both sourced from CONAPO. All specifications include the following control variables: 1) Region: fixed effects for eight broad regions in Mexico; 2) Demographics: 1990 CZ demographics, including the share of men and the share of people with primary education as their highest level; 3) Industry: shares of employment in manufacturing in 1990 and the 1990 level of employment-to-population ratio. All regressions are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to heteroskedasticity and clustered by state. The coefficients marked with ∗∗∗, ∗∗, and ∗ are significant at the 1%, 5%, and 10% confidence levels, respectively.

	(1) Sexual Crime	(2) Family Violence	(3) Property Crimes
Exposure to domestic robots	-0.248	-1.592	0.214
	(0.152)	(1.011)	(1.342)
Exposure to foreign robots	0.0309	0.126	-0.184
	(0.0500)	(0.547)	(0.402)
Share of routine workers in 1990	1.076	-9.278	23.32
	(3.270)	(19.85)	(15.86)
Exposure to Chinese import competition	0.143**	0.873**	0.534
	(0.0597)	(0.389)	(0.776)
Exposure to tariff changes from NAFTA	11.75	140.5*	1.131
	(15.01)	(81.17)	(66.84)
Change in employment-to-population ratio 00-15	-0.00705	0.0102	0.141*
	(0.0153)	(0.0900)	(0.0777)
Demographics	✓	✓	✓
Industry	✓	✓	✓
Region	✓	✓	✓
Observations	1802	1802	1802
R^2	0.498	0.586	0.521
F	26.11	10.43	9.364
Kleibergen-Paap Wald F-stat	172.7	172.7	172.7

Table A.7: Impact of exposure to robots on other crimes associated with the Death of Despair hypothesis (IV).

Notes: The dependent variable in column 1 refers to the homicide rate, while column 2 refers to the number of these types of crimes per 10,000 population, both sourced from CONAPO. All specifications include the following control variables: 1) Region: fixed effects for eight broad regions in Mexico; 2) Demographics: 1990 CZ demographics, including the share of men and the share of people with primary education as their highest level; 3) Industry: shares of employment in manufacturing in 1990 and the 1990 level of employment-to-population ratio. All regressions are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to heteroskedasticity and clustered by state. The coefficients marked with $***$, $**$, and $*$ are significant at the 1%, 5%, and 10% confidence levels, respectively.

A.5 Results: Politics

	(1) Sheinbaum (Left)	(2) Galvez (Right)	(3) Alvarez (Center)	(4) Null
External exposure to domestic robots	0.0192	-0.0164	-0.00280	0.000837
	(0.0119)	(0.0132)	(0.00443)	(0.000602)
External exposure to foreign robots	0.00716**	-0.00446	-0.00267*	0.000172
	(0.00275)	(0.00282)	(0.00150)	(0.000191)
Share of routine workers in 1990	-0.580***	0.682***	-0.104	-0.00225
	(0.143)	(0.148)	(0.0842)	(0.0178)
Exposure to Chinese import competition	-0.00679	0.00169	0.00499*	-0.000132
	(0.00585)	(0.00579)	(0.00267)	(0.000328)
Exposure to tariff changes from NAFTA	1.427**	-1.370**	-0.0561	-0.00429
	(0.603)	(0.586)	(0.302)	(0.0716)
Change in employment	-0.000698	-0.0000398	0.000743	-0.0000801
	(0.00101)	(0.000949)	(0.000487)	(0.0000812)
Share of men in 1990	0.420	-0.179	-0.240**	0.0558
	(0.425)	(0.404)	(0.115)	(0.0449)
Share of people with primary education in 1990	0.119	-0.210**	0.0922*	-0.0272**
	(0.110)	(0.0966)	(0.0510)	(0.0122)
Share of manufacturer workers in 1990	-0.0307	0.0448	-0.0136	-0.00160
	(0.0874)	(0.0714)	(0.0481)	(0.00742)
Employment to population 1990	0.00133	-0.00172	0.000375	-0.000325***
	(0.00149)	(0.00126)	(0.000623)	(0.000110)
Region	✓	✓	✓	✓
Observations	1800	1800	1800	1800
R^2	0.534	0.420	0.292	0.328

Table A.8: Effect of Robot Exposure on Electoral Outcomes in 2024 elections (OLS Estimates)

Notes: The dependent variables in columns 1–3 represent each candidate's share of valid votes. Column 4 reports the share of null votes relative to the total number of votes cast. All specifications include the following control variables: 1) Region: fixed effects for eight broad regions in Mexico; 2) Demographics: 1990 CZ demographics, including the share of men and the share of people with primary education as their highest level; 3) Industry: shares of employment in manufacturing in 1990 and the 1990 level of employment-to-population ratio. All regressions are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to heteroskedasticity and clustered by state. The coefficients marked with ∗ ∗ ∗, ∗∗, and ∗ are significant at the 1%, 5%, and 10% confidence levels, respectively.

A.6 Robustness Check - Distance to the US

	(1) Sheinbaum (Left)	(2) Galvez (Right)	(3) Alvarez (Center)	(4) Null
Exposure to domestic robots	0.0184*	-0.0157	-0.00275	0.000800
	(0.0107)	(0.0120)	(0.00414)	(0.000558)
Exposure to foreign robots	0.00786***	-0.00489*	-0.00294*	0.000189
	(0.00279)	(0.00296)	(0.00159)	(0.000202)
Share of routine workers in 1990	-0.593***	0.692***	-0.101	-0.00274
	(0.139)	(0.145)	(0.0817)	(0.0173)
Exposure to Chinese import competition	-0.00785	0.00231	0.00542**	-0.000155
	(0.00557)	(0.00572)	(0.00269)	(0.000335)
Exposure to tariff changes from NAFTA	1.444**	-1.389**	-0.0542	-0.00315
	(0.577)	(0.566)	(0.291)	(0.0695)
Change in employment	-0.000754	-0.00000311	0.000763	-0.0000816
	(0.000973)	(0.000916)	(0.000477)	(0.0000787)
Share of men in 1990	0.418	-0.176	-0.241**	0.0557
	(0.413)	(0.394)	(0.113)	(0.0439)
Share of people with primary education in 1990	0.126	-0.214**	0.0896*	-0.0270**
	(0.106)	(0.0940)	(0.0500)	(0.0119)
Share of manufacturer workers in 1990	-0.0172	0.0353	-0.0175	-0.00118
	(0.0826)	(0.0688)	(0.0461)	(0.00723)
Employment to population 1990	0.00144	-0.00180	0.000349	-0.000321***
	(0.00146)	(0.00123)	(0.000605)	(0.000107)
Region	✓	✓	✓	✓
Observations	1800	1800	1800	1800
R^2	0.544	0.428	0.294	0.328
F	44.48	51.58	16.85	17.36
Kleibergen-Paap Wald F-stat	172.7	172.7	172.7	172.7

Table A.9: Effect of Robot Exposure on Electoral Outcomes in 2024 elections (IV Estimates)

Notes: The dependent variables in columns 1–3 represent each candidate's share of valid votes. Column 4 reports the share of null votes relative to the total number of votes cast. All specifications include the following control variables: 1) Region: fixed effects for eight broad regions in Mexico; 2) Demographics: 1990 CZ demographics, including the share of men and the share of people with primary education as their highest level; 3) Industry: shares of employment in manufacturing in 1990 and the 1990 level of employment-to-population ratio. All regressions are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to heteroskedasticity and clustered by state. The coefficients marked with $***$, $**$, and $*$ are significant at the 1%, 5%, and 10% confidence levels, respectively.

	(1) Morena (Left)	(2) Pan - PRI (Right)	(3) Null
External exposure to domestic robots	0.00200	-0.00430	0.000598
	(0.00391)	(0.00391)	(0.000493)
External exposure to foreign robots	0.00277***	-0.00337***	0.000254**
	(0.00100)	(0.00100)	(0.000127)
Share of routine workers in 1990	-0.440***	0.486***	-0.00905
	(0.0684)	(0.0685)	(0.00865)
Exposure to Chinese import competition	0.00273*	-0.00178	-0.000437**
	(0.00145)	(0.00145)	(0.000183)
Exposure to tariff changes from NAFTA	1.482***	-1.469***	-0.0744*
	(0.319)	(0.319)	(0.0403)
Change in employment-to-population ratio 00-15	0.000188	-0.000628	-0.000119*
	(0.000527)	(0.000527)	(0.0000666)
Demographics	✓	✓	✓
Industry	✓	✓	✓
Region	✓	✓	✓
Observations	1802	1802	1802
R^2	0.717	0.591	0.538

Table A.10: Effect of Robot Exposure on Electoral Outcomes in 2018 and 2024 elections pooled (OLS Estimates)

Notes: The dependent variables in columns 1 and 2 represent each candidate's share of valid votes. Column 3 reports the share of null votes relative to the total number of votes cast. All specifications include the following control variables: 1) Region: fixed effects for eight broad regions in Mexico; 2) Demographics: 1990 CZ demographics, including the share of men and the share of people with primary education as their highest level; 3) Industry: shares of employment in manufacturing in 1990 and the 1990 level of employment-to-population ratio. All regressions are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to heteroskedasticity and clustered by state. The coefficients marked with $***$, $**$, and $*$ are significant at the 1%, 5%, and 10% confidence levels, respectively.

	(1) Morena (Left)	(2) Pan - PRI (Right)	(3) Null
Exposure to domestic robots	0.00213	-0.00437	0.000591
	(0.00367)	(0.00367)	(0.000464)
Exposure to foreign robots	0.00302***	-0.00368***	0.000278**
	(0.00108)	(0.00108)	(0.000136)
Share of routine workers in 1990	-0.440***	0.487***	-0.00927
	(0.0675)	(0.0675)	(0.00853)
Exposure to Chinese import competition	0.00228	-0.00124	-0.000477**
	(0.00151)	(0.00151)	(0.000191)
Exposure to tariff changes from NAFTA	1.481***	-1.470***	-0.0738*
	(0.314)	(0.314)	(0.0397)
Change in employment-to-population ratio 00-15	0.000164	-0.000598	-0.000121*
	(0.000520)	(0.000520)	(0.0000657)
Demographics	✓	✓	✓
Industry	✓	✓	✓
Region	✓	✓	✓
Observations	1802	1802	1802
R^2	0.718	0.593	0.539
F	112.0	63.96	51.32
Kleibergen-Paap Wald F-stat	16449.2	16449.2	16449.2

Table A.11: Effect of Robot Exposure on Electoral Outcomes in 2018 and 2024 elections pooled (IV Estimates)

Notes: The dependent variables in columns 1 and 2 represent each candidate's share of valid votes. Column 3 reports the share of null votes relative to the total number of votes cast. All specifications include the following control variables: 1) Region: fixed effects for eight broad regions in Mexico; 2) Demographics: 1990 CZ demographics, including the share of men and the share of people with primary education as their highest level; 3) Industry: shares of employment in manufacturing in 1990 and the 1990 level of employment-to-population ratio. All regressions are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to heteroskedasticity and clustered by state. The coefficients marked with $***$, $**$, and $*$ are significant at the 1%, 5%, and 10% confidence levels, respectively.

	(1)	(2)	(3)
	Δ Left	Δ Right	Δ Null
External exposure to domestic robots	0.0141	-0.00204	0.00228
	(0.0661)	(0.0144)	(0.0261)
External exposure to foreign robots	0.0615***	-0.0118**	-0.00297
	(0.0188)	(0.00490)	(0.00630)
Share of routine workers in 1990	3.195*	0.778***	0.311
	(1.598)	(0.237)	(0.355)
Exposure to Chinese import competition	-0.0841**	0.00525	-0.00960
	(0.0391)	(0.00725)	(0.00604)
Exposure to tariff changes from NAFTA	-11.85	-0.974	-2.242
	(7.999)	(0.582)	(1.760)
Change in employment-to-population ratio 00-15	0.00810	-0.00108	0.000791
	(0.0117)	(0.00152)	(0.00244)
Demographics	✓	✓	✓
Industry	✓	✓	✓
Region	✓	✓	✓
Observations	1792	1792	1788
R^2	0.295	0.579	0.327

Table A.12: Effect of Robot Exposure on Electoral Outcomes in Changes between 2000 - 2024 elections pooled (OLS Estimates)

Notes: The dependent variables in columns 1 and 2 measure the change in each party family's share of valid votes between 2000 and 2024. Column 3 reports the change in the share of null votes relative to total votes cast. All specifications include the following control variables: 1) Region: fixed effects for eight broad regions in Mexico; 2) Demographics: 1990 CZ demographics, including the share of men and the share of people with primary education as their highest level; 3) Industry: shares of employment in manufacturing in 1990 and the 1990 level of employment-to-population ratio. All regressions are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to heteroskedasticity and clustered by state. The coefficients marked with $***$, $**$, and $*$ are significant at the 1%, 5%, and 10% confidence levels, respectively.

	(1)	(2)	(3)
	Δ Left	Δ Right	Δ Null
Exposure to domestic robots	0.0183	-0.00289	0.00194
	(0.0624)	(0.0132)	(0.0241)
Exposure to foreign robots	0.0672***	-0.0129**	-0.00324
	(0.0203)	(0.00531)	(0.00674)
Share of routine workers in 1990	3.198**	0.777***	0.310
	(1.537)	(0.227)	(0.338)
Exposure to Chinese import competition	-0.0945**	0.00724	-0.00908
	(0.0386)	(0.00699)	(0.00652)
Exposure to tariff changes from NAFTA	-11.93	-0.957*	-2.232
	(7.776)	(0.554)	(1.689)
Change in employment-to-population ratio 00-15	0.00758	-0.000975	0.000815
	(0.0113)	(0.00146)	(0.00238)
Demographics	✓	✓	✓
Industry	✓	✓	✓
Region	✓	✓	✓
Observations	1792	1792	1788
R^2	0.295	0.582	0.327
F	241.2	15.86	128.7
Kleibergen-Paap Wald F-stat	384.0	384.0	384.0

Table A.13: Effect of Robot Exposure on Electoral Outcomes in Changes between 2000 - 2024 (IV Estimates)

Notes: The dependent variables in columns 1 and 2 measure the change in each party family's share of valid votes between 2000 and 2024. Column 3reports the change in the share of null votes relative to total votes cast. All specifications include the following control variables: 1) Region: fixed effects for eight broad regions in Mexico; 2) Demographics: 1990 CZ demographics, including the share of men and the share of people with primary education as their highest level; 3) Industry: shares of employment in manufacturing in 1990 and the 1990 level of employment-to-population ratio. All regressions are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to heteroskedasticity and clustered by state. The coefficients marked with $***$, $**$, and $*$ are significant at the 1%, 5%, and 10% confidence levels, respectively.

	(1)	(2)
	# Strikes	# Strikes
Exposure to domestic robots	-0.00605	-0.00622
	(0.0206)	(0.0194)
Exposure to foreign robots	-0.0115**	-0.0129**
	(0.00493)	(0.00546)
Pre-Shock Strikes (1999)	0.105***	0.105***
	(0.00108)	(0.00109)
Share of routine workers in 1990	1.071***	1.087***
	(0.375)	(0.372)
Exposure to Chinese import	-0.00281	-0.000691
	(0.00693)	(0.00737)
Exposure(NAFTA)	3.985**	3.995**
	(1.699)	(1.685)
Change in employment-to-pop	-0.0162***	-0.0162***
	(0.00299)	(0.00297)
Demographics	✓	✓
Industry	✓	✓
Region	✓	✓
Observations	1805	1805
R^2	0.950	0.950
F	1894.5	1896.5
Kleibergen-Paap Wald F-stat		14284.4

Table A.14: Impact of exposure to robots on the number of strikes.

Notes: The dependent variable is the number of strikes initiated (huelgas estalladas, INEGI). The variation refers to the period 1999 and 2016. Column (1) reports OLS estimates, and Column (2) reports IV estimates. All specifications include the following controls: (i) Region: fixed effects for eight broad regions in Mexico; (ii) Demographics: 1990 CZ demographics, including the share of men and the share of individuals with only primary education; (iii) Industry: 1990 employment shares in manufacturing and the 1990 employment-to-population ratio. All regressions are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to heteroskedasticity. The coefficients marked with $***$, $**$, and $*$ are significant at the 1%, 5%, and 10% confidence levels, respectively.

	(1)	(2)	(3)
	Sheinbaum (Left)	Galvez (Right)	Alvarez (Center)
Exposure to domestic robots	0.0196*	-0.0170	-0.00259
	(0.0102)	(0.0117)	(0.00418)
Exposure to foreign robots	0.00747**	-0.00444	-0.00301*
	(0.00311)	(0.00316)	(0.00164)
Distance to US	-0.0000421	0.0000485	-0.00000663
	(0.0000898)	(0.0000814)	(0.0000217)
Share of routine workers in 1990	-0.569***	0.664***	-0.0971
	(0.140)	(0.150)	(0.0801)
Exposure to Chinese import competition	-0.00894*	0.00359	0.00523*
	(0.00543)	(0.00592)	(0.00285)
Exposure to tariff changes from NAFTA	1.425***	-1.364**	-0.0613
	(0.538)	(0.532)	(0.289)
Change in employment-to-population ratio 00-15	-0.000514	-0.000264	0.000785*
	(0.000903)	(0.000893)	(0.000470)
Share of men in 1990	0.445	-0.205	-0.239**
	(0.410)	(0.391)	(0.112)
Share of people with primary education in 1990	0.113	-0.200**	0.0877*
	(0.0986)	(0.0902)	(0.0496)
Share of manufacturer workers in 1990	-0.0147	0.0324	-0.0172
	(0.0837)	(0.0699)	(0.0465)
Employment to population 1990	0.00142	-0.00177	0.000346
	(0.00149)	(0.00127)	(0.000604)
Region	✓	✓	✓
Observations	1800	1800	1800
R^2	0.547	0.431	0.293
F	71.59	49.35	19.83
Kleibergen-Paap Wald F-stat	165.0	165.0	165.0

Table A.15: Effect of Robot Exposure on Electoral Outcomes in 2024 elections (IV Estimates), adding distance to the US as a control variable

Notes: The dependent variables in columns 1–3 represent each candidate's share of valid votes. All specifications include the following control variables: 1) Region: fixed effects for eight broad regions in Mexico; 2) Demographics: 1990 CZ demographics, including the share of men and the share of people with primary education as their highest level; 3) Industry: shares of employment in manufacturing in 1990 and the 1990 level of employment-to-population ratio. All regressions are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to heteroskedasticity and clustered by state. The coefficients marked with $***$, $**$, and $*$ are significant at the 1%, 5%, and 10% confidence levels, respectively.

	(1)	(2)	(3)
	Δ Left	Δ Right	Δ Null
Exposure to domestic robots	0.0227	-0.00448	0.00124
	(0.0660)	(0.0135)	(0.0259)
Exposure to foreign robots	0.0633**	-0.0123**	-0.00521
	(0.0248)	(0.00568)	(0.00681)
Distance to US	-0.000362	0.0000681	-0.000151
	(0.000747)	(0.0000891)	(0.000125)
Share of routine workers in 1990	3.220**	0.774***	0.322
	(1.505)	(0.227)	(0.342)
Exposure to Chinese import competition	-0.0990***	0.00829	-0.0105
	(0.0381)	(0.00713)	(0.00700)
Exposure to tariff changes from NAFTA	-11.56	-1.036*	-2.117
	(8.060)	(0.567)	(1.729)
Change in employment-to-population ratio 00-15	0.00795	-0.00114	0.000615
	(0.0109)	(0.00142)	(0.00246)
Demographics	✓	✓	✓
Industry	✓	✓	✓
Region	✓	✓	✓
Observations	1792	1792	1788
R^2	0.295	0.582	0.329
F	26.26	144.6	140.6
Kleibergen-Paap Wald F-stat	325.7	325.7	325.7

Table A.16: Effect of Robot Exposure on Electoral Outcomes in Changes between 2000 - 2024 (IV Estimates), adding distance to the US as a control variable

Notes: The dependent variables in columns 1 and 2 measure the change in each party family's share of valid votes between 2000 and 2024. Column 3 reports the change in the share of null votes relative to total votes cast. All specifications include the following control variables: 1) Region: fixed effects for eight broad regions in Mexico; 2) Demographics: 1990 CZ demographics, including the share of men and the share of people with primary education as their highest level; 3) Industry: shares of employment in manufacturing in 1990 and the 1990 level of employment-to-population ratio. All regressions are weighted by a CZ's share of the national working-age population in 1990. Standard errors are robust to heteroskedasticity and clustered by state. The coefficients marked with $***$, $**$, and $*$ are significant at the 1%, 5%, and 10% confidence levels, respectively.